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How much do online consumers really value free product returns? Evidence from eBay

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ABSTRACT

Consumer return rates have been steadily rising in recent years, resulting in growing costs for retailers who must manage the returns process and the disposition of returned products. This cost pressure is driven in part by extremely generous return policies, such as giving consumers a full refund upon return. Interestingly, this common retail practice of full refunds is inconsistent with the recommendations of many analytical models of returns, which nearly always show that a partial refund is optimal. Such inconsistencies between theory and practice might arise when the decision drivers included in the analytical models do not match the decision drivers in practice. It might also be the case that retailers are overly optimistic about the value that consumers assign to a full refund, and thus assume that the value of such a policy outweighs its costs. In this paper, we use data collected from eBay, where identical products are sold with different return policies, to investigate these open questions in the literature. We analyze both the return policy drivers from the retailer's perspective and the return policy value from the consumer's perspective. Our results suggest that the value of a full refund policy to consumers may not be as large as one might expect, and it also exhibits a large heterogeneity across buyers with different levels of online purchase experience. In addition, we provide empirical evidence for what has long been suspected by online retailers – that a non-refundable forward shipping charge quickly erodes any value that consumers assign to return policies. The generality of our results is limited by the fact that eBay differs from traditional retail contexts in many respects, including the fact that eBay buyers may not be representative of the general buyer population. However, our study of how eBay consumers value free returns provides new insights into an understudied area, and it can serve as a starting point for future studies of the value of return policies in other retail contexts.

1. Introduction

An important business challenge for many retailers is the processing of consumer returns, i.e. products that consumers return within the retailer's pre-specified, and often "no-questions-asked," return window. Consumer returns are different than retailer overstock returns (to the manufacturer) and end-of-use returns by consumers (typically occurring after many months or years of use). The cost of consumer returns is significant. In 2015, the value of all consumer returns received by U.S. retailers was estimated at $260.5 billion, an increase of approximately 50% from 2007 (National Retail Federation, 2008; Ng and Stevens, 2015). A comparable magnitude of increase has also been observed for return rates in the past decade (National Retail Federation, 2008, 2016), from below 10% to around 14%. After returns are accepted by retailers, additional costs such as inspection, return logistics, and refurbishment or disposal will incur at various steps along the "reverse supply chain," accounting for 5–6% of a typical OEM's revenue and 4% of a typical retailer's sales (Douthit et al., 2011). It is reported that the returns-associated reverse logistics costs alone are $40 billion for the retail sector (Enright, 2003). Moreover, if returned products are sold to external liquidators and outlet stores, their salvage value is often only 10%–20% of the original retail price (Stock et al., 2006). As a result, the management of consumer returns has become one

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of the top managerial challenges faced by U.S. retailers according to an industry study by UPS (Brill, 2015).

A significant contributor to the increasing volume (and cost) of consumer returns is the popular trend of adopting lenient return policies. In the past, restocking fees were common among consumer electronic retailers such as mail-order computer dealers (Chu et al., 1998). Today, however, almost all major retailers offer a full refund. For example, Best Buy lifted their 15% restocking fee on consumer electronics in 2010 (Reisinger, 2010), while Wal-Mart has long been offering a 90-day full refund policy. Clearly, retailers generally believe that a full refund is the best return policy despite the significant costs that offering such a policy entails. Given their unwillingness to reduce the refund amount, most retailers simply focus on preventing and managing returns through efforts such as (1) reducing consumer product uncertainty *before purchase*, e.g. through buyer assistance programs and virtual fitting technology, and (2) streamlining the operations of the reverse supply chain *after the return* (see Pinçe et al. (2016) for a recent example).

Spurred by the magnitude of the costs involved in managing returns, academic researchers have produced a number of papers on the topic. The vast majority of this work has been analytical, with several models investigating the optimal return policies under various product, market, and consumer characteristics. For example, Shulman et al. (2009) study a monopoly retailer selling multiple products, while Hsiao and Chen (2012) consider a broad notion of quality risk, which encompasses product uncertainty – a common reason for returns – as a component. In sharp contrast to practice, these theoretical results almost always recommend a *partial refund*, that is, a refund of only a fraction of the original price.[1] This is also true in studies that examine the effect on a retailer's return policy decision from competition (Shulman et al., 2011), manufacturer-retailer coordination (Su, 2009), the joint decisions of return policy and inventory (Ketzenberg and Zuidwijk, 2009), open-box sales (Akçay et al., 2013), and end-of-season markdown pricing (Altug and Aydinliyim, 2016).

At a high level, there are two possible explanations for the discrepancy between the recommendations from the theoretical literature (which advises offering partial refunds) and actual retail practice (offering full refunds). First, it might be that the decision drivers included in the analytical models, whose goal is to provide high-level insights, do not closely match the decision drivers used in practice. That is, the stylized representations of reality in these models might be inconsistent with how retail managers actually make decisions regarding return policies. Indeed, although analytical models of the decision can be quite complex, anecdotal evidence from industry surveys and news articles suggests that the reason for choosing full over partial refund in practice can be quite simple. For example, a majority of consumers review return policies before purchase (Hsiao and Chen, 2012) and dislike any return-related fees (O'Neill and Chu, 2003), influencing retailers to claim that offering a lenient return policy is simply necessary to keep them competitive (Chao, 2015). A second possible explanation is that retailers may be overly optimistic about the value that consumers assign to a full refund, and thus assume (perhaps incorrectly) that the value of such a policy outweighs its costs. While the specific return-related costs (e.g. reverse logistics costs) are relatively easy to quantify for a retailer, the value that consumers attribute to a return policy is more difficult to measure. Given the limited empirical evidence on the return policy value, it is difficult for retailers to make informed decisions regarding the relative costs and benefits of offering full refunds.

This study contributes to the consumer returns literature by offering empirical insights on both the benefits from offering a full refund and the possible drivers behind this important decision for the retailer in the eBay context. First, using eBay auction data where multiple retailers sell the same products through the same channel but with different return policies, we present an assessment of whether the three return policy drivers assumed in the analytical literature (specifically: competitive environment, product salvage value, and retailer reputation) influence an eBay retailer's return policy choices. Secondly, we leverage the eBay auction data to estimate the value of a full refund policy to consumers using its impact on the final auction prices. In the extant literature, Anderson et al. (2009) was the first to attempt to empirically quantify the value of a return policy in the context of a mail-order apparel retailer, which only offers a full refund for all of the products sold. The approach used in their paper is to fit a structural choice model to catalog apparel sales (revealed preference data) and approximate the decrease in the consumer's utility when no refund was offered by using counterfactual analysis. Because their data is only from a single retailer that does not change its return policy during the time of the study, a counterfactual analysis is the only option available for their study. Heiman et al. (2015) provide another estimate for apparel products through a survey (stated-preference data) where consumers are asked about the discount they are willing to accept if the return policy is hypothetically removed. As described in detail below, both our data and our empirical approach are significantly different from these previous studies since we study revealed-preference data in a setting where different retailers sell the exact same products, but some offer full refunds while others offer no refund. The presence of different retailers offering different return policies allows us to provide a more direct comparison. Moreover, our focus on the eBay context enables us to examine the extent to which the non-refundable shipping charge might be perceived as a "latent restocking fee" by consumers. In addition, we examine how more experienced eBay shoppers might better estimate their cost of product uncertainty and hence assign a larger value to a full refund policy. This consumer heterogeneity aspect adds an important nuance to our findings that has not been previously explored.

We provide a brief overview of our research goals and approach here. Our focus is on small to medium size online retailers (SMEs), as represented by our dataset of eBay sellers. For SMEs that face the decision of what type of return policy to offer, we provide an estimate of the additional dollar value that consumers place on a product sold with versus without a full refund policy. Since the retailers should be able to more easily estimate their internal costs of offering full refunds, our estimate of the benefit side of the equation should enable them to make more informed decisions. For retailers who have already made the decision to offer free returns, we provide an estimate of the premium they can charge for their products when competing against similar retailers that do not offer free returns.

To help answer our research questions, we collected data on consumer electronics products sold through eBay auctions. We chose eBay as our data source due to the fact that it includes *identical* products sold with *different* return policies (i.e. full refund vs. no refund) through different sellers which are mostly small to medium in size. The reason for our focus on consumer electronics is two-fold. First, the National Retail Federation (2016) estimates that return rates for "hard goods," including consumer electronics, are 50% more than the grand average across product categories, while return rates from online sales are twice as large as in brick-and-mortar stores (Ng and Stevens, 2015). Second, an examination of the return policies of major online electronics retailers and

[1] Full refund does appear as an optimal solution under certain conditions, such as when product cost and salvage value are both zero, and degree of product differentiation are medium in Shulman et al. (2009, see Case 2 in Table 4).

Table 1
Return policies of online consumer electronics retailers.

Company	Refund for product price	Refund for forward shipping (if not free)	Who pays for return shipping
Panel A: online stores of major retailers[a]			
Wal-Mart	full refund	no refund	consumer
Target	full refund	no refund	retailer
Amazon[b]	full refund	no refund	consumer
Best Buy	full refund	not clear	consumer
Sears	up to 15% restocking fee	no refund	consumer
Panel B: direct channel of representative manufacturers			
Dell	up to 15% restocking fee	no refund	consumer
HP	full refund	no refund	consumer
Sony	up to 15% restocking fee	no refund	consumer
Lenovo	15% restocking fee	no refund	consumer
Shure	full refund	no refund	consumer
Panel C: our data source			
ebay[c]	mostly full refund	no refund	mostly consumer

[a] We include the top five consumer electronic retailers on the “2013 Top 100 Retailer” chart published by National Retail Federation. Return policy information was accessed on May 2014.
[b] Most of the Amazon marketplace sellers use the same return policy as Amazon.
[c] In principle, sellers on eBay could specify their own return policy terms. Our observation is that most sellers fully refund the product price but do not refund shipping charges.

manufacturer-direct channels reveals that it is a common practice not to refund the forward shipping charge[2] (Table 1), making our analysis on the role of shipping charge particularly relevant.

The key econometric challenge we face in measuring the impact of a return policy by comparing the final bid prices of the same product sold with and without a full refund is that return policies are not randomly assigned to retailers. Instead, it is reasonable to assume that retailers select the return policy they think will be most effective for them - i.e. the return policy decision is likely to be endogenous. We address this endogeneity issue using a control variable approach, leveraging a wide variety of variables collected to help understand return policy drivers, as well as insights from a rich body of previous empirical studies that have utilized eBay data. A second challenge is the appropriate interpretation of eBay bidding behavior and final auction prices. That is, we must consider whether a buyer's bid in an eBay auction reveals his true valuation for the product. Although this has been a standard assumption in the literature (e.g. Bajari and Hortaçsu, 2003; Cabral and Hortaçsu, 2010; Subramanian and Subramanyam, 2012) due to the similarity of the auction format on eBay to a second-price English auction, Zeithammer and Adams (2010) challenge this assumption by showing that auction participants sometimes bid less than their true valuations (“bid $<$ value”) due to the reactive bidding style. Following the insights of Zeithammer and Adams (2010), we supplement our main analysis with an analysis on a sub-sample of auctions where the “bid $=$ value” assumption is most likely to hold and show that our main findings continue to hold.

We find that, when determining return policies, retailers on eBay appear to consider both the product salvage value and their own reputation/quality. Contrary to the assumptions of some analytical papers on this topic, however, we do not find evidence that retailers consider the competitive intensity when making their return policy decision. While the value of a full refund to eBay consumers is positive and significant, we find that its magnitude is not as large as one might expect and is considerably lower than the 20–30% for catalog and in-store apparel products estimated by Anderson et al. (2009) and Heiman et al. (2015). Moreover, forward shipping charges erode this positive impact rapidly, suggesting that consumers consider non-refundable forward shipping charges as a “latent” restocking fee - a finding that is commonly suspected by industry professionals but never before empirically validated. We also find that the full refund policy value varies widely across buyers with different levels of online purchase experience.

In interpreting our results, an important word of caution is needed regarding our use of eBay data, despite the desirable features of this empirical context discussed above. The eBay environment is substantially different from traditional retail contexts. In particular, eBay buyers may not necessarily be representative of the general population of buyers (which this study does not explore). Thus, there is a risk of sample selection bias for buyers who may self-select out of eBay due to the inherently higher-risk environment of having to return a faulty/disliked product.[3] Therefore, we cannot directly generalize our insights to a traditional retailer's return policy, such as Wal-Mar's 90-day unconditional guarantee.

Our use of eBay data for a study of returns also requires a discussion of eBay's platform-wide Money-Back-Guarantee (MBG), which exists for all transactions, regardless of the seller's return policy. Importantly, we note that this coverage is only for “an item that is not received or as described” (eBay, 2016b), which is unambiguously communicated to buyers. Thus, the eBay MBG is not applicable for returns due to dissatisfaction, which are instead covered by the return policies of the seller. It is the value of these seller return policies that we endeavor to quantify in this study. One should note that a buyer may still attempt to use eBay's MBG to return a disliked item when a seller's return policy does not accept returns (that is, by filing a fraudulent claim). However, there is no indication or evidence that such fraudulent behavior is systemic among eBay buyers, as supported by a recently published large-scale study (Hui et al., 2016). Still, we acknowledge that some buyers may attempt to abuse eBay's MBG by filing false claims. Such claims, which would be quite challenging to track or measure, could hypothetically influence a seller's attempt to gauge the benefits of offering a return policy.

Despite the above caveats and limitations regarding working with eBay data, our research provides new insights into the value of

[2] For completeness, we check their practice on assigning return shipping charges, which is also found to primarily be a no refund policy. Since a return shipping charge is often paid for by the consumer rather than being set by the retailer, it is less interesting from a managerial perspective and can be viewed as an exogenous cost that is relatively constant across all consumers.

[3] We thank an anonymous reviewer for bringing this point to our attention.

free returns beyond what is currently available in the literature. We believe that these insights can act as a starting point for future studies in this area that move beyond the eBay context.

2. Literature review and hypotheses

A number of analytical models of consumer returns have been developed in the academic literature, where the return policy decision is generally assumed to be driven by some combination of three main factors. We begin by discussing the theory behind each of these drivers, followed by a discussion of how the value that consumers assign to a full refund policy is affected by forward shipping charges and a buyer's previous online purchase experience.

2.1. Drivers of return policies

The first driver of a retailer's return policy that we consider is *competitive intensity*. Analytical models of consumer returns under competition show that a retailer's optimal return policy is influenced by the number of competitors (Altug and Aydinliyim, 2016) and their return policy choices (Shulman et al., 2011). This seems reasonable, since anecdotal evidence also suggests that retailers consider pressure from competitors who offer generous refunds as one of the main reasons to offer lenient return policies despite the high cost of processing returns (Chao, 2015). When identical products are sold by multiple retailers on the same marketplace such as eBay, it is conceivable that retailers are more likely to accept returns when the competition for doing so is more intense. At the time of listing a product, eBay retailers observe a wealth of information that characterizes this competitive intensity, including the number of existing offerings of the same product from other retailers, whether they offer return policies, and the prices of the current and just-ended product listings.

The second driver that we consider is the salvage value of a returned product, which partially determines how costly it is for a retailer to accept returns. Specifically, Su (2009) demonstrates that a monopoly retailer should set its refund equal to the salvage value if consumers are *ex ante* homogeneous and their product uncertainty can be stylized as a continuous distribution. Using this result as a benchmark, Akçay et al. (2013), Altug and Aydinliyim (2016), and Shang et al. (2017) discuss how retailers should modify the refund amount when there is an "open-box" sales opportunity, when the retailer employs markdown pricing for end-of-season inventories, and when a fraction of the market is made up by opportunistic consumers, respectively. An alternative consumer utility formulation that dichotomizes product uncertainty into two scenarios – match and mismatch – suggests that the optimal refund is a function of the salvage value (Hsiao and Chen, 2012; Chu et al., 1998). In practice, the salvage value for a given electronic product might vary widely depending on how the retailer handles the returned units. For example, Groupon, the daily deals website, recovers around one-fourth of a product's wholesale price when using Genco's liquidating service, while reselling the same returned product online directly to consumers might generate a recovery of 40%–70% of the product's wholesale price (Ng and Stevens, 2015). Although the true salvage value is private knowledge to eBay retailers, we capture a retailer's resell cost and potential options for salvaging returned products through a number of proxy variables.

The third driver that we consider is the retailer's reputation. As an important service attribute attached to a product, a return policy often serves as a signal of the more opaque aspects of retailer quality, such as the security of the transaction and speed of order processing. Thus, more reputable retailers are more likely to offer a full refund policy, a theoretical result shown in Moorthy and Srinivasan (1995). The signaling role of offering a full refund policy is even more salient in the online shopping environment since this environment lacks the store ambiance cues available at brick-and-mortar retailer stores (Biswas and Biswas, 2004). The literature offers insights on the relationship between retailer reputation and return policy choice at an aggregate level. Specifically, Bonifield et al. (2010) demonstrate a significant correlation between an aggregate online retailer rating provided by BizRate.com and a return policy leniency index that describes a retailer's overall returns practice across all products. We provide a deeper analysis of the effect of reputation on return policy value in two ways. First, we examine return policies attached to the same product by different retailers. Second, we not only use general reputation indices such as feedback score and customer ratings, but also a return-specific reputation measure extracted from the text of retailer review comments.

The following Hypothesis summarizes these three return policy drivers:

Hypothesis 1. *A retailer is more likely to offer a full refund policy when (a) the competition is more intense, (b) the product salvage value is higher, and (c) its reputation is stronger.*

2.2. Value of full refund return policies in auctions

Since a consumer's valuation for a product is determined by its service attributes as well as its physical attributes, it is commonly assumed that the contribution of each attribute in forming this aggregate value of valuation is additively separable (Rosen, 1974). That is, if we take away a service attribute, such as the full refund policy, the consumer valuation for the product decreases by a quantity that is equal to the value of the full refund policy. Let V_1 and V_0 denote the total value of a product with and without a full refund policy, respectively. Then, $V = V_1 - V_0$ corresponds to the full refund policy value. Utilizing this idea, Heiman et al. (2002) analytically explore the conditions under which it is better for the retailer to "unbundle" the return policy from the product and sell it separately, similar to the option of purchasing an extended warranty. Empirically, additive separability has been used to understand consumers' valuation of warranty services (Chu and Chintagunta, 2009) and remanufactured products (Subramanian and Subramanyam, 2012), among others. In the following, we hypothesize how V is contingent on the shipping charge and buyer experience. While we state our hypotheses in terms of the full refund policy *value*, we use the differences in the final *auction prices* as a proxy for this value.

2.3. Non-refundable shipping charge

When a return is deemed necessary, a full refund typically means that a consumer receives a refund for the total price paid, but is not reimbursed for any forward shipping charges that were incurred. For example, if a digital camera is purchased for \$300 plus a \$50 forward shipping charge, the refundable amount is \$300, not \$350. This is a common practice for the online retailers of consumer electronics (see Table 1), including the retailers on eBay (unless a consumer receives an item not matching the description on the product listing page, in which case all charges are refunded directly by eBay under its MBG). Given that most buyers of consumer electronics have a non-trivial (perceived) probability of returning a purchased item, the calculation of V needs to incorporate the non-refundable shipping charge. The higher the shipping charge, the more loss a consumer will potentially incur, which in turn reduces their valuation for the product V. In other words, the forward shipping charge would be considered by a rational consumer as an "implicit restocking fee." Indeed, several analytical models of consumer returns (Hess et al., 1996; Chu et al., 1998) assume that non-refundable shipping and handling charges imposed by online retailers are part of the *de facto* restocking fee. We analyze the effect of the forward shipping charge empirically and quantify its impact:

Hypothesis 2. *Buyers' perceived value for a product's full refund policy decreases with the non-refundable forward shipping charge of that product.*

2.4. Online purchase experience

While the value of a full refund policy is associated with service attributes such as a shipping charge, it is also likely to exhibit heterogeneity across buyers. We explore this heterogeneity from the perspective of the consumers' previous online purchase experience on eBay. Following the literature, we argue that the more experienced consumers are different from their less experienced peers, which in turn leads to a higher perceived value of a full refund policy. First, since return policies allow consumers to allocate more fit-assessing effort to the post-purchase stage, it reduces the consumers' pre-purchase information search (Urbany et al., 1989). Wood (2001) shows experimental evidence that consumers' deliberation time for a purchase decision is shorter in the presence of a lenient return policy, such as a full refund. The degree to which consumers suppress their product information search is likely to be higher for those who pay frequent visits to the online retailer, given their lower cognitive cost of making a purchase decision at the retailer (Johnson et al., 2003). Second, the way consumers assign value to a lenient refund policy is complicated by the fact that they must estimate a product's "misfit" probability (Shulman et al., 2015). Consumers make adjustments to this probability over time through repeated purchase and possibly returns (Gu and Tayi, 2015). Since more experienced online shoppers realize product uncertainty to a larger degree (Liang and Huang, 1998), it is reasonable to believe that the less experienced shoppers tend to under-estimate the probability of a product "misfit", which leads to the following Hypothesis:

Hypothesis 3. *Buyers with more previous online purchase experience have a higher perceived value for a product's full refund policy.*

3. Empirical setting

In this section, we first discuss our data collection process and product selection criteria, as well as a summary of variables. Next, we investigate eBay seller's return policy switching behavior, which provides important insights into what constitutes the appropriate sample for return policy driver analysis and how to address the potential endogeneity problem in estimating the value of a return policy to consumers. Lastly, we present summary statistics for variables used in the subsequent return policy driver and value analyses.

3.1. Data collection and variable description

We retrospectively collect data on the completed listings of selected products from eBay on May 15, June 14, and July 14 of 2015 for a 30-day interval each. Since eBay keeps sold and unsold listings available for 90 and 30 days respectively (eBay, 2016c), these three data retrievals allow us to reconstruct the sold listings of a product between February 14 and July 14, and unsold listings between April 16 and July 14.

There are several aspects to consider in selecting the products for our analysis. First, the product needs to be popular enough to ensure a reasonable sample size. Second, the product should not have many configurations/versions. These two motivations are consistent with the literature (e.g. Cabral and Hortaçsu, 2010, p. 58). Third, the product should require some hands-on experience for most consumers to determine its exact fit to their needs. Lastly, the products chosen should have relatively similar price levels, making a pooled analysis more reliable. Specifically, we collect data for GoPro Hero 4 (Black and silver), Xbox One (with and without Kinect), and Bose QC25[4] – a total of five versions from three different products. While these products are not necessarily the optimal choice, they reflect the set of characteristics we look for in our analysis.

Fig. 1 depicts the data collection steps and summarizes the type of information collected at each step. Appendix A expands this description with screen shots for the typical web pages, and a detailed discussion on the data collection steps and data cleaning issues. Note that on top of the return policy specified on a listing page by the retailer (captured by the *ReturnPolicy* variable as discussed next), eBay as the online retail platform also provides its MBG on all listings (which applies only for "an item that is not received or as described" as discussed in the Introduction).

Table 2 presents the variables in our analysis (we provide detailed descriptions of variable construction in Appendix B). While *ReturnPolicy* is used as the dependent variable in the return policy driver analysis (H1), *Price* and *Second Price* are the dependent variables in both our main and robustness return policy value analyses (H2 and H3), where *ReturnPolicy*[5] is the focal independent variable of interest. We use the next three groups of variables to test the significance of the return policy drivers hypothesized in H1. While the retailer reputation variables are straightforward, we elaborate on the competitive intensity and product salvage value variables as follows. For a particular product, the competitive intensity variables encompass the availability, price, and return policy of the same product from other retailers on eBay. We create two types of measures to reflect the possibility that when an eBay retailer lists the item, she might form her impression of the competitive surroundings either by checking the live listings ("live" measures) or by researching recently completely listings (e.g. those within the past day – "day" measures). While there exists a broader competitive environment for eBay retailers outside the eBay channel, this environment is relatively static in terms of product availability and return policies offered. For example, large retailers such as Amazon and BestBuy almost always have these popular electronic products in stock and did not change their return policies during the time of our study. In addition, the price variation in the "external" environment is likely to be positively correlated with the price variation within eBay. Therefore, our treatment of only considering the competitive intensity inside the eBay channel is expected to capture the majority of the relevant changes in the competitive environment for eBay retailers. We capture product

[4] GoPro Hero 4 is a high-end sports camcorder. At the time of our data collection, two main versions existed on the official website, silver priced at $399.99 and black at $499.99. Although Xbox One appears to have many versions (mostly due to the different games being bundled), the main difference is whether Kinect is included with the game console. The manufacturer's price on its website for the version with Kinect is $449, and for the one without Kinect is $349. Bose QC25 is the newest noise-cancellation headphone from Bose, the official channel price for which is $299.

[5] A typical retail return policy would also specify a return time window and a restocking fee. We observe that about 95% of the return-accepted auctions in our sample has a 14-day window (the default option; other options include 7, 30 and 60 days). Thus, we do not distinguish return time window in our analysis. In addition, although retailers can add a restocking fee in the listing description, we observe only a negligible fraction of listings that show restocking fees, which are discarded.

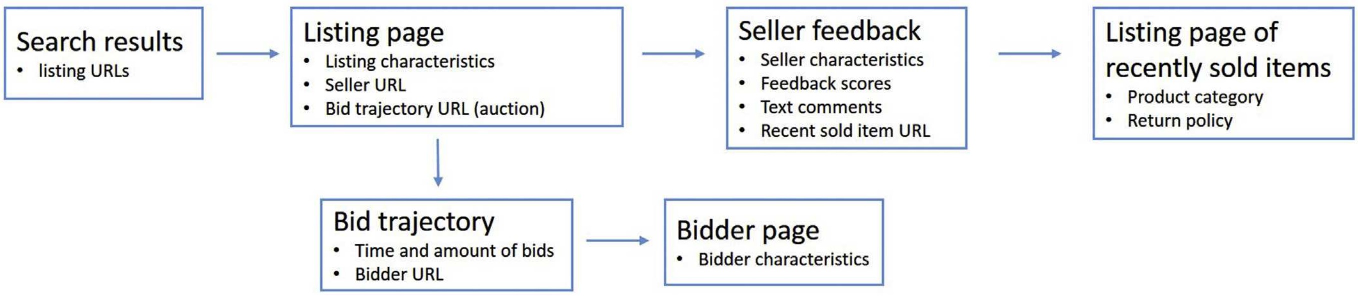

Fig. 1. Data collection process.

Table 2
List of variables for return policy analysis.

Variable name	Definition
Auction Price and Return Policy	
Price	Total price paid by auction winner, including shipping charge
SecondPrice	Total price consists of top bid from the second highest bidder and shipping charge
ReturnPolicy	Whether retailer offering full refund (1) or no refund (0)
Competitive Intensity ("Live" and "Day" Measures)	
NumListLive(Day)	# of active (completed in the past day) listings of the same new product
AvgPriceLive(Day)	Average price of active (sold in the past day) listings of the same new product
LowPriceLive(Day)	Lowest price among active fixed-price (sold in the past day) listings of same new product
PctFullLive(Day)	% of active (completed in the past day) listings of the same new product with full refund return
Product Salvage Value	
Store	Whether retailer operates an eBay store (1) or not (0)
TotalFb12(6)	# of retailer feedbacks in the past 12(6) months
Posi(Nega)Fb12	# of positive (negative and neutral) retailer feedbacks in the past 12 months
NumElecFb	# of retailer feedbacks associated with consumer electronics in the past 3 months
Retailer Quality/Reputation	
CommuRate	0-5 rating on retailer communication with buyers
ReturnFbRatio	% of return-related positive retailer feedbacks
CommuFbRatio	% of communication-related positive retailer feedbacks
Listing Characteristics	
ShipCharge	$ of shipping charge given the chosen class of shipping service
ShipService	Expedited (1) or economy (0) shipping
Images	# of pictures on the listing page
DesLength	# of letters (in thousands) of the text in the product description area
TitleSkill	# of "attractive words" in the listing title/subtitle, from 0 to 4
Price-Determining Bidder Characteristics	
BuyerExp	# of auctions participated in the past 30 days
BidderFb	100% positive feedback (1) or otherwise (0)
BidAtSeller	Whether participated in an auction by the seller in the past 30 days (1) or not (0)
Auction Dynamics	
AuctionDuration	Length of the auction – 1, 3, 5, 7, or 10 days
StartingBid	$ of starting auction price, as low as $0.01
Bidders	# of bidders participated
Bids	# of bids received
Other Control Variables	
SellerYear	Time difference in years from the retailer's registration date to 01/01/2015
RevisedFb	# of retailer feedbacks revised by the buyer
Workday	Whether auction ended during a workday (1) or weekend (0)
Daytime	Whether auction ended between 6am and 6pm (1) or not (0)
Month	Month of the year, ranging from February (2) to July (7)

salvage value through the *Store* variable and various feedback volume measures. The store status on eBay decreases the cost of re-listing a returned item, and large volume sellers in general should have better capability and more channels to dispose of returned products, both implying a higher salvage value. Given that feedback volume has been shown to be proportional to the sales volume (Cabral and Hortaçsu, 2010, p.64), we use feedback volume as a proxy for sales volume. Lastly, we note that *ShipCharge* and *BuyerExp* are used to test H2 and H3 through their interaction terms with *ReturnPolicy*.

3.2. Retailer's return policy switching behavior

The appropriate sample for investigating return policy drivers depends on whether and how frequently eBay retailers switch their return policies. Consider an eBay retailer who sells a particular product N times. For the first time, she needs to explicitly make a choice on the return policy (i.e., full versus no refund). For the following $N-1$ times, she might adopt one of two possible approaches when specifying the return policy. First, she can simply carry the previous return policy choice over without active assessment, which is a straightforward process given eBay's "copy

Table 3
The extent of Retailer's return policy switching behavior.

# of Listings	# of RP Changes	GoPro			Xbox One		
		Bose	Black	Silver	Kinect	No Kinect	Pooled
1	N/A	184	738	890	848	522	2769
[2,5]	0	104	471	434	380	227	1470
	≥ 1	**4**	**7**	**8**	**10**	**7**	**31**
[5,10]	0	22	57	62	43	22	204
	≥ 1	**2**	**6**	**0**	**4**	**1**	**16**
≥ 11	0	14	30	18	13	15	114
	≥ 1	**1**	**1**	**0**	**0**	**1**	**8**
Among Sellers with >1 Listings							
# Engaged in ≥ 1 RP Changes		7	14	8	14	9	55
% Engaged in ≥ 1 RP Changes		4.76%	2.45%	1.53%	3.11%	3.30%	2.98%
Total RP Change Points		617	1741	1539	1186	915	6532
# Actual RP Changes		7	18	10	16	9	74
% Actual RP Changes		1.13%	1.03%	0.65%	1.35%	0.98%	1.13%

listing" feature (eBay, 2016e). In this case, return policy stays static within the retailer (i.e., no dynamics over time) and hence, we should focus our driver analysis on her first listing of our products. Second, she could actively *re-evaluate* the adequacy of the previous return policy choice and make the switch-or-stay decision. If such re-evaluation rarely results in a return policy change, our focus should still be on the first listing. Otherwise, the $N-1$ subsequent listings needs to be included in the sample. Therefore, regardless of the return policy decision approach (i.e., passive carryover or active re-evaluation), we need to examine whether retailers switch their return policy (for the same product) over time. If they do, it is also important for us to know the frequency of this change.

We compute a variety of summary statistics in Table 3 to examine the extent of retailers' return policy changes over time. For each of the five products, we categorize retailers according to two criteria: number of listings and instances of return policy change.[6] For example, for GoPro Black, there are 738 retailers with only one listing for whom a return policy change cannot exist. Thus, the "# of RP Changes" column has a value of "N/A." For retailers with two or more listings, who we separate into three buckets (those with 2–5, 6 to 10, and more than 11 listings), a return policy change is possible. As a result, we further split each bucket into two sub-buckets based on whether at least one instance of return policy change is observed (0 indicating no and ≥ 1 indicating yes). The number of retailers in the ≥ 1 sub-buckets are highlighted in bold (e.g., 7, 6, and 1 for GoPro Black). Then, we summarize the data by two statistics among the retailers with >1 listings: the total number and percentage of retailers (e.g., 14 and 2.45%, respectively, for GoPro Black) having engaged in at least one instance of return policy change. Finally, we look into the frequency of return policy changes. To do this, we change the unit of analysis from retailers to "potential return policy change points." As discussed earlier, for a retailer who have listed a product N times, she has $N-1$ subsequent opportunities to adjust the initial return policy choice, that is, $N-1$ potential return policy change points (no potential change point if $N=1$). For example, for GoPro Black, there are 1741 such potential change points and 18 (or 1.03%) actual changes. The other four products in our sample show similar results. Overall, these statistics provide strong empirical evidence that a retailer rarely changes her return policy for a given product over time (at least within a period of three months). We also compute another set of statistics under the "Pooled" column, which lumps all five products together with the assumption that the retailer treats these products the same when setting her return policies. Even under this liberal assumption, there are only 2.98% retailers who have ever engaged in return policy switching, and only 1.13% actual return policy changes over the potential change points.

To see whether the above conclusion holds more generally, we collect additional data regarding retailers' sold items (other than the five products in our sample) over the past 90 days, aggregate them at the category level (instead of product level), and compute similar summary statistics as above. While details of this analysis is presented in Appendix C to conserve space, our conclusion is highly consistent: there is only a small fraction of eBay retailers who change their return policies (for the same product category) over time and even if they do, the frequency is very low. As a result, we focus our return policy driver analysis on retailers' first listings. To do this, we need to tease out a sample of "first-time" retailers such that their initial listings of our five products are observed in the data, which is discussed in the next section.

The analysis of return policy switching behavior also offers important insights regarding the level at which we should focus our efforts for addressing return policy endogeneity when estimating the value of a full refund in §4.3. Specifically, since our data has an auction-within-retailer structure,[7] we need to understand whether the endogeneity problem exists at the retailer level or the auction level. This is because the appropriate correction approach depends on the level of endogeneity (Westerlund, 2005). Since most eBay retailers do not change their return policy choice over time, we conclude that the potential endogeneity problem should concentrate at the retailer-level, not the auction-level, which is often referred to as cross-sectional endogeneity in the literature (e.g. Mark et al., 2005). This approach of identifying the level of endogeneity is in line with prior studies (e.g. van Dijk et al., 2004; Leenheer et al., 2007). A full discussion of our approach to address the return policy endogeneity is provided in §4.2.

[6] Both auction and fixed-price format listings are included here, since it is conceivable that for the same product, a retailer might not distinguish the return policy decision based on listing format. By pooling together both listings formats, we are able to observe a larger set of retailers who might engage in return policy changes, as well as a larger sample of potential return policy change points.

[7] Given the similarity between the second-price English auction and the auction format on eBay, many prior studies (e.g. Bajari and Hortaçsu, 2003; Cabral and Hortaçsu, 2010; Subramanian and Subramanyam, 2012) make the implicit assumption that "bid = value". This means employing final auction price, Price, as the dependent variable provides us with the desirable interpretation of the ReturnPolicy coefficient as the value of a full refund policy to consumers. When quantifying the value of a full refund policy, our sample includes only auctions (no fixed-price listings).

3.3. Sample construction and summary statistics

Using the insights garnered above, we now construct two samples, one for testing H1 (driver sample) and the other for H2 and H3 (value sample), and present the variable summary statistics in each sample respectively. Starting with the driver sample, as mentioned above, we first need to carve out the subset of first-time retailers from the 4612 total retailers observed in our sample. We discuss two methods to discern first-time retailers. For the first method, recall that our first data retrieval from eBay was on 05/15/2015. Since eBay keeps the sold listings visible for 90 days (eBay, 2016c), our data should contain a retailer's first listing (of the five products in our sample) if she registered on eBay on or after 02/15/2015 (i.e., 90 days before the first data retrieval). Using this rule, we obtain a total of 324 such retailers, which we label as "absolute first-time retailers."

One potential problem with this method could be that while the resulting sample is clean, its size is small, which might not entail high enough power to detect significance for some of the variables. To address this concern, we consider a second method. Instead of using registration dates, we use the listing titles of a retailer's commented sold items to make an educated guess on how likely this retailer has listed a given product in the past. Specifically, for each comment on a retailer's feedback page, we observe the title of the listing being commented on (see Figure OA.1 for example). After extracting all titles, we use a string matching algorithm to check whether any one of these titles contain any format of the three words – bose, gopro, and xbox. If not, we consider the retailer a "likely first-time retailer" for the products in our sample. While it is possible that we might miss some retailers who have sold these products for which buyers did not comment on, this approach significantly increases the number of potential first-time retailers since any retailer with feedback can qualify under this method, regardless of their registration date. Accordingly, we identify a total of 2579 likely first-time retailers.

Given the complementarity between the driver sample constructed from absolute and likely first-time retailers, we conduct return policy driver analysis on both samples. Since the results are by and large consistent, in the following, we focus the presentation of variable summary statistics (in Panel A of Table 4) and regression results (in §4.1) from the larger, likely first-time retailer sample, and delegate those from the absolute first-time retailer sample to robustness checks in §5. Since only the first listing from each retailer is included, our sample size is 2579 – one observation per retailer. Note that a negative SellerYear is possible, since some retailers register after January 2015. We also note that the data availability for the competitive intensity variables is lower than the rest, since these variables can be constructed only for listings posted after a time threshold. For the same reason, the live measures of competitive intensity is less available than the day measures (see Appendix B for details).

Next, we turn to the sample for return policy value analysis, which includes all sold auctions from retailers who do not switch their return policies (i.e. all but the 55 return policy changers identified in the last column of Table 3). Variable summary statistics are presented in Panel B of Table 4. The exclusion of return policy changers is in line with our effort for addressing return policy endogeneity at the retailer-level. Essentially, we are neglecting the *possible but minimal* endogeneity at the auction-level.[8] To be cautious, we demonstrate through a robustness check in §5 that all of our main results hold when adding back these auctions from the return policy changers.

We provide a detailed look into the key variables of interest (*ReturnPolicy, ShipCharge,* and *BuyerExp*) by product in Table 5. For both the GoPro and Xbox products, a full refund is offered on 20%–30% of the auctions, while the rate for the Bose products is noticeably higher at 40%. Across all products, 25%–40% of the auctions offer free shipping. Among the ones that charge for shipping, the average *ShipCharge* is about \$10 for Bose and GoPro, and about \$20 for Xbox. The difference is likely due to the latter's larger physical dimensions. Regarding buyer experience, we observe that GoPro and Xbox buyers have bid on an average of 17 items in the past 30 days, while Bose buyers only bid on an average of 5 items in the past 30 days. We also compute the average total price paid in the no-return and the return-accepted auctions, as well as the differential, which represents a crude estimate on the impact of offering a full refund policy. Not surprisingly, the return-accepted auctions register a higher average price for all products, with the differential for Xbox sales noticeably higher than the other two products.

Fig. 2 shows histograms for *ShipCharge* and *BuyerExp*. We observe that *BuyerExp* appears to be exponentially distributed and has a fairly long tail. Thus, we log-transform it for our analysis to accommodate the expectation that the marginal effect at large values should be much smaller.[9] We also observe that both *ShipCharge* and *BuyerExp* show a small fraction of large values, which motivates us to perform several robustness checks in §5.2. As it is a common practice in the literature (Melnik and Alm, 2002; Subramanian and Subramanyam, 2012) to separate positive and negative reviews for estimating auction price, we include both *PosiFb12* and *NegaFb12*, and log-transform them for our analysis.

4. Main results

In this section, we first empirically examine what drives an online retailer's return policy choice and test Hypothesis 1. Then, before moving on to quantifying the value of a full refund policy and testing Hypothesis 2 and 3, we devote a detailed discussion to the endogeneity concern of return policy and our solution.

4.1. Testing the drivers of a return policy

For the three theoretical drivers of return policy choice, we start with competitive intensity. Correlations between the competitive intensity variables (both live and day measures) and the return policy are all very low – smaller than 0.05 and insignificant. Next, using a logistic regression framework, we enter the live measures of competitive intensity one at a time (upper half of Table 6). None of the four variables is significant. The same procedure for the day measures yields similar results (lower half of Table 6). Combining this result with our previous return policy switching statistics, our analysis shows no support that retailers choose their return policies according to competitive intensity (for the first and the subsequent listings). Thus, Hypothesis 1a is *not supported*.

Unlike competitive intensity, the correlations between *ReturnPolicy* and variables for the other two drivers—salvage value and

[8] In a linear regression framework, the magnitude of the endogeneity bias is determined, among other factors, by how much variation in the endogenous regressor is explained by the unobserved sources of endogeneity (Rossi, 2014, p.657). Since retailers rarely change their return policies over time, there is little variation of this endogenous regressor at the auction level that can be explained by any potential sources of endogeneity. Therefore, focusing the return policy endogeneity at the retailer level while neglecting the auction-level endogeneity is not likely to result in much bias.

[9] For example, when BuyerExp increases from 0 to 10, its impact should be much more pronounced than an increase from 100 to 110. For the same reason, we also log-transform TotalFb12, TotalFb6, and FbScore.

Table 4
Variable summary statistics.

Panel A: Sample for Return Policy Driver Analysis											
	N	Mean	St.	Min	Max		N	Mean	St.	Min	Max
ReturnPolicy	2579	0.2	0.4	0	1	LowPriceDay	2480	325.8	49.1	200	494
SellerYear	2579	5.7	5.2	−0.5	18.4	PctFullDay	2480	0.4	0.2	0	1
Competitive intensity						**Salvage value**					
NumListLive	1516	78	23.7	2	121	Store	2579	0.1	0.3	0	1
AvgPriceLive	1516	408.3	47.9	251.9	479.5	TotalFb12	2579	326.4	4174.40	0	141,854
LowPriceLive	1516	330.2	51.2	200	420	NumElecFb	2579	2.6	18.8	0	586
PctFullLive	1516	0.4	0.1	0	0.8	**Seller reputation/quality**					
NumListDay	2480	13.5	5.7	1	36	CommuRate	2579	1.3	2.1	0	5
AvgPriceDay	2480	374.3	44.2	235.7	494	ReturnFbRatio	2579	0.01	0.1	0	1
Panel B: Sample for Return Policy Value Analysis											
	N	**Mean**	**St.**	**Min**	**Max**		**N**	**Mean**	**St.**	**Min**	**Max**
TotalPrice	3139	367.9	53.8	205.2	595.8	**Listing characteristics**					
ReturnPolicy	3139	0.2	0.4	0	1	ShipCharge	3139	10.6	11.1	0	91.9
Time-related factors						Images	3139	3.1	2.3	1	12
Workday	3139	0.7	0.5	0	1	DesLength	3139	7	1.1	4.7	12.5
Daytime	3139	0.8	0.4	0	1	TitleSkill	3139	0.8	0.7	0	4
Month	3139	4.4	1.5	2	7	**Seller characteristics**					
Auction process						SellerYear	3139	6.8	5.1	−0.5	17.4
Bidders	3139	7.6	4.9	1	29	Store	3139	0.1	0.3	0	1
Bids	3139	17.7	15.3	1	100	PosiFb12	3139	2014.80	13,130.70	0	100,029
AuctionDuration	3139	4.4	2.6	1	10	NegaFb12	3139	4.9	27.2	0	204
StartingBid	3139	201.4	141	0.01	580	NumElecFb	3139	17.1	39.5	0	322
Bidder characteristics						CommuRate	3139	2.4	2.4	0	5
BidItems	3139	10.6	42.2	0	530	ReturnFbRatio	3139	0.01	0.1	0	1
BidderFb	3139	0.9	0.3	0	1	RevisedFb	3139	0.1	0.6	0	9
BidAtSeller	3139	0.5	0.5	0	1						

Table 5
Summary statistics for key variables by product (sample for return policy value analysis).

	Bose	GoPro		Xbox One	
		Black	Silver	Kinect	No Kinect
N	206	918	981	594	440
% ReturnPolicy = 1	40.3%	24.1%	21.3%	28.5%	22.7%
% ShipCharge = 0	40.3%	36.6%	36.3%	24.2%	28.0%
Avg. ShipCharge if > 0	$10.80	$12.18	$11.13	$22.16	$24.86
Avg. BuyerExp if > 0	5.0	16.8	14.2	17.0	15.7
Avg. TotalPrice if ReturnPolicy = 0	$255.47	$422.39	$351.99	$369.65	$328.33
Avg. TotalPrice if ReturnPolicy = 1	$258.84	$425.44	$356.39	$382.60	$339.01
Price differential	$3.37	$3.05	$4.40	$12.95	$10.68
	1.32%	0.72%	1.25%	3.50%	3.25%

N = 3139. The percentage price differentials are calculated as price differential divided by average price if ReturnPolicy = 0.

retailer reputation—are much higher. In Table 7, we enter these variables one at a time and find each of them to be significant through the likelihood ratio test. When all variables are entered in Model (D13), the significance level remains unchanged for all but *LogTotalFb12*, which becomes marginally significant. Recall that *NumElecFb* captures a retailer's sales volume for consumer electronics products, while *LogTotalFb12* captures total sales. Thus, one plausible explanation is that category-specific sales is a better proxy for salvage value and hence, the additional variation in the retailers' return policy choices explained by overall sales is only marginal. In the last column of Table 7, we compute Average Marginal Effect (AME) for each variable of interest that is statistically significant based on Model (D13). Since *Store* is a binary variable, its AME measures the probability of offering a full refund policy for retailers without a store status versus those with one. For the other continuous variables, the AME is based on the partial derivative of full refund probability with respect to each variable. The interpretation for the AME of *CommuRate* (0.016), for example, is that one unit of increase in communication rating is associated with 0.016 increase in the probability of choosing full refund. Considering the different range of these variables (e.g. *ReturnFbRatio* bounded by 0 and 1, while *CommuRate* by 0 and 5), the AMEs suggest a moderate-to-large practical effect size of the salvage value and retailer reputation variables. Overall, these findings provide strong evidence in support of Hypothesis 1b and 1c for retailers' first listings. Recall that salvage value and retailer reputation variables remain fairly static over time and hence should not explain return policy choice beyond the first listings.

Taken together, our return policy drivers analysis reveals that eBay retailers do not consider the full array of factors suggested in analytical studies when setting their return policies, which might in part contribute to the gap between the theoretical recommendation of a partial refund versus the common retail practice of offering full refunds. We acknowledge that the return policies in our study (i.e. the two extremes: no refund and full refund) do not cover the full spectrum often considered in analytical models (i.e. restocking fee from 0% to 100%), which might also explain the gap. Our analysis also reveals, however, that return policy choices do not appear to be as “simplistic” as they are sometimes described in the popular press (e.g. Chao, 2015). For example, among the retailer reputation

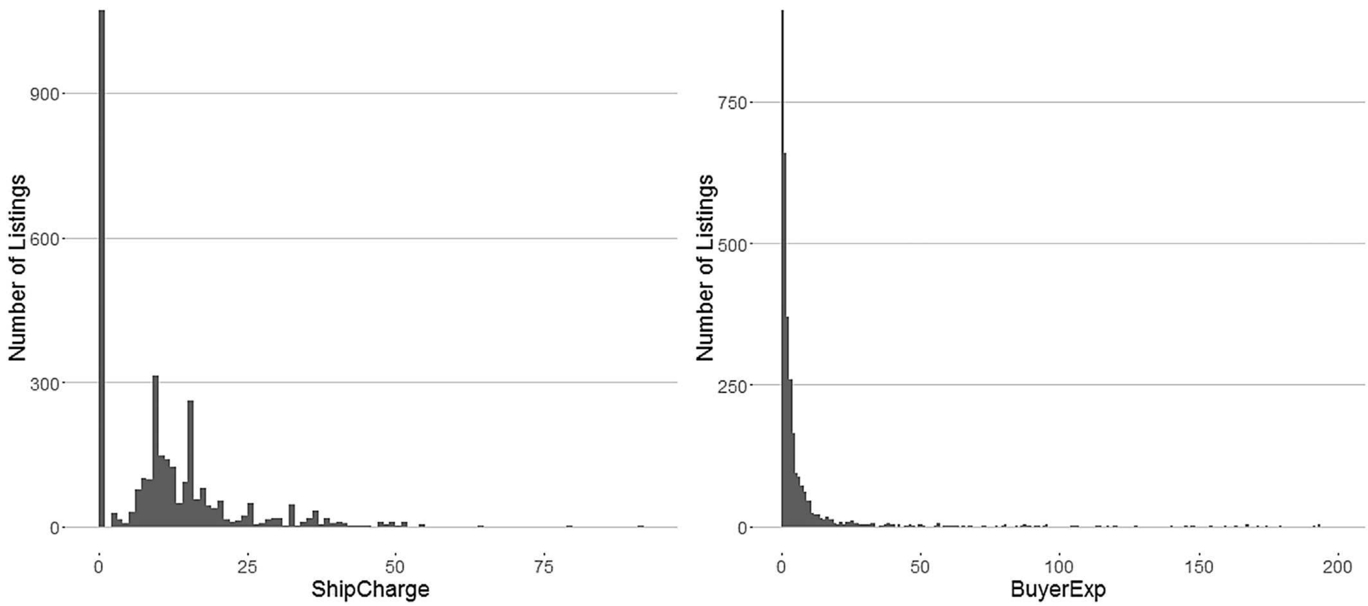

Fig. 2. Histograms of shipping charge and buyer experience.

Table 6
Logistic regression for the impact of competitive intensity on return policy choice.

	Model (D1)	Model (D2)	Model (D3)	Model (D4)
NumListLive	0.003 (0.004)	0.005 (0.005)	0.007 (0.005)	0.006 (0.005)
AvgPriceLive		−0.013 (0.010)	−0.019 (0.011)	−0.019 (0.011)
LowPriceLive			0.005 (0.003)	0.005 (0.003)
PctFullLive				1.022 (1.007)
Product FE	Included	Included	Included	Included
Constant	−0.721* (0.309)	2.882 (2.804)	3.179 (2.802)	2.837 (2.821)
N	1516	1516	1516	1516
LL	−762.346	−761.518	−760.356	−759.841
LR Test	0.559	1.655	2.324	1.031
	Model (D5)	**Model (D6)**	**Model (D7)**	**Model (D8)**
NumListDay	−0.0002 (0.011)	0.0001 (0.011)	−0.001 (0.011)	−0.001 (0.011)
AvgPriceDay		−0.001 (0.003)	0.00004 (0.004)	0.0001 (0.004)
LowPriceDay			−0.001 (0.002)	−0.001 (0.002)
PctFullDay				0.255 (0.308)
Product FE	Included	Included	Included	Included
Constant	−0.201248	−0.446 (0.905)	−0.377 (0.911)	−0.485 (0.921)
N	2480	2480	2480	2480
LL	−1252.17	−1252.137	−1251.948	−1251.604
LR Test	0.000	0.065	0.378	0.687

*$p < 0.05$. Prefix "D" in model numbering stands for driver analysis. The "LR Test" rows show likelihood ratio test results (χ^2 statistics) for the newly added variable. For example, LR Test for Model (D1) compares its likelihood with that of its nested model (i.e. removing NumListLive.), yielding a χ^2 statistic of 0.559, insignificant at 0.1 level. In fact, none of the LR Test results are significant at the 0.1 level.

variables, *ReturnFbRatio* is not *immediately* accessible to the retailer, since it requires frequent tracking of what the buyers post in feedback texts. Our results suggest that such monitoring of feedback does influence return policy decisions.

Next, we turn to quantifying the value of a full refund policy to consumers and testing H2 and H3. The key econometric challenge is addressing endogeneity in the *ReturnPolicy* variable. Thus, we devote the next section to the discussion of this endogeneity issue before moving on to the empirical results in §4.3.

4.2. Addressing return policy endogeneity: reasons and solution

Using eBay auctions, we attempt to uncover the value of a full refund policy through a regression framework with final price paid in the auction, *Price*, as the dependent variable, and return policy choice, *ReturnPolicy*, as the key independent variable. Endogeneity concerns under this empirical framework might arise due to two reasons: reverse causality from past prices to current return policy choice[10], and omitted variable bias caused by unobserved common drivers of *ReturnPolicy* and *Price*. In the following, we first discuss

[10] Due to the nature of how an eBay auction listing is first generated by a retailer, then bid on by one or more potential buyers, and finally won by the highest bidder, the issue of simultaneity—another type of reverse causality—is unlikely to exist in eBay auctions. Moreover, per eBay's restrictions on revising listings (eBay, 2016d), as soon as an auction receives its first bid, most of the listing specifications cannot be changed. Our own attempts to change the return policy during the bidding process confirms this.

Table 7
Logistic regression for the impact of salvage value and retailer reputation on return policy choice (N = 2579).

	Model (D9)	Model (D10)	Model (D11)	Model (D12)	Model (D13)	AME
SellerYear	−0.023* (0.01)	−0.039*** (0.011)	−0.038*** (0.011)	−0.035** (0.011)	−0.032** (0.011)	
Store	2.479*** (0.158)	1.882*** (0.182)	1.808*** (0.186)	1.719*** (0.187)	1.708*** (0.187)	0.340
LogTotalFb12		0.201*** (0.033)	0.172*** (0.034)	0.085* (0.043)	0.082† (0.043)	0.011
NumElecFb			0.018* (0.008)	0.017* (0.008)	0.017* (0.008)	0.002
CommuRate				0.111*** (0.033)	0.117*** (0.033)	0.016
ReturnFbRatio					2.308*** (0.561)	0.317
Product FE	Included	Included	Included	Included	included	
Constant	−0.868*** (0.229)	−1.317*** (0.244)	−1.281*** (0.245)	−1.203*** (0.247)	−1.264*** (0.248)	
LL	−1178.76	−1159.64	−1154.27	−1148.60	−1140.55	
LR Test	281.248***	38.257***	10.729**	11.335***	16.109***	

†$p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Numbering of model continue from Table 6. The "LR Test" rows show likelihood ratio test results (χ^2 statistics) for the newly added variable. For example, LR Test for Model (D9) compares its likelihood with that of its nested model (i.e. removing Store.), yielding a χ^2 statistic of 281.248, significant at 0.001 level. The "AME" column presents the Average Marginal Effect.

why reverse causality is unlikely to be the primary concern for endogeneity. Focusing on omitted variable bias, we next explain why collecting additional relevant variables and including them as controls is the most appropriate strategy to address endogeneity in our context.

Recall from our analysis on return policy switching behavior that the endogeneity concern concentrates at the retailer-level. Thus, we investigate whether the reverse causal relationship, "past prices → current return policy choice," exists for a retailer's first listing of a product (i.e. no subsequent switching). There are two interpretations of what may constitute the past price construct. The first is a retailer's own past price—price of the same product sold in the past. However, for the first listing of a product, there is no own past price. Therefore, only the second interpretation—price of the previously sold items from other retailers in the market—is relevant. This interpretation of past price is captured by the two price-related variables of competitive intensity, namely *AvgPriceLive* and *LowPriceLive* (or their day measure counterparts). Empirical results from the previous section demonstrate that neither variable significantly influences *ReturnPolicy*. Therefore, reverse causality from price to return policy is unlikely to be the primary concern of endogeneity in our context.

Omitted variable bias—the other potential reason for endogeneity—arises when some factors that are not included in the regression equation may influence the final auction price and at the same time correlate with the retailer's return policy choice. To mitigate the omitted variable bias, we closely follow the consumer returns literature and the empirical studies using eBay data to construct two sets of relevant variables that, if not controlled for, have a fair chance of inducing omitted variable bias. The first set includes proxy variables for product salvage value and retailer reputation. Their impact on return policy choice are shown above, while their impact on auction prices has been shown in the literature (e.g. Cabral and Hortaçsu, 2010; Houser and Wooders, 2006). The second set includes listing characteristics that manifest the latent selling skill of the retailer, where skilled sellers might be more likely to accept returns while realizing higher auction prices. To capture a retailer's latent selling skill, we follow a number of recent eBay-based studies that explore this topic (e.g. Lei, 2011; Melnik and Alm, 2002) and construct *Images*, *TitleSkill*, and *DesLength*.

In the following, we discuss why using control variables is the most appropriate way to address omitted variable bias in our context. Card (1999) discusses three common strategies to address endogeneity in observational data: using comparable units to form quasi-experiments, employing instrumental variables, and collecting control variables to proxy the source of omitted variable bias. The viability of the first strategy is highly dependent on context. For example, the usual candidates that qualify as comparable units in educational economics are siblings, twins, and parent-children pairs (Card, 1999). We are not aware of a natural way to define retailers with such close resemblance on eBay. Reliability of estimates produced from the second strategy, using instrumental variables, highly depends on the quality of the instrument. A quality instrument needs to be both *relevant*, i.e., strongly correlated with return policy, and *exogenous*, i.e., not directly correlated with auction price (except indirectly through its effect on return policy). However, our prior analyses as well as contextual knowledge indicate that a quality (external) instrument is unlikely to exist. For example, we can exploit the fact that return policy is determined at the start of an auction while price is determined at the end, and that an auction on eBay usually lasts more than a few days. Thus, we can look for factors exhibiting strong inter-temporal dynamics and measured at the start of the auction, such as *LowPriceLive* and *AvgPriceLive* used above, as potential instruments. Since the other listings that are "live" might change substantially from the start to the end of an auction, we could reasonably assume that *LowPriceLive* and *AvgPriceLive*, while observed by the retailer, are not observable to the price-determining buyer of the auction, and the *exogeneity* condition would hold. Unfortunately, these variables are unlikely to be *relevant*, since we have shown that they affect neither the first time nor the subsequent return policy choices. Alternatively, we could consider potentially *relevant* variables, such as listing and retailer characteristics that correlate with return policy choice. However, these factors are directly visible to the buyer and hence the *exogeneity* condition is unlikely to hold. Note that when good external instrumental variables are not available, one could construct internal instruments to address *endogeneity* using approaches such as in Lewbel (2012). However, since the endogenous *regressor* in our context, *ReturnPolicy*, has little within-retailer variation (evident from Table 3), proper results are not guaranteed.[11] The above discussion on the implausibility of a valid instrument, together with the fact that the validity of an instrument may not be verified through statistical tests (Deaton, 2010, p.431), leads us to refrain from using the instrumental variable approach. Indeed, as Ketokivi and McIntosh (2017) state in a recent paper: "*Applying instrumental variables amounts to trading one set of untestable assumptions for another, and using a bad instrument may well make things worse than sticking to OLS … This observation offers a segue to the next candidate solution to tackling endogeneity: instead of trying to come up with better models, perhaps an actionable answer lies in getting better*

[11] We thank the anonymous Associate Editor for bringing this point to our attention.

data."

This brings us to the third strategy, collecting control variables to proxy the source of omitted variable bias, which is fortunately both viable and appropriate for our context. Specifically, we are able to identify the level at which the omitted variable bias might exist, and the factors that might contribute to this bias if omitted. Moreover, our analysis of return policy drivers as well as the existing literature on eBay provide important insights on how to directly measure and control for these factors. In the absence of strong instruments, Rossi (2014, p.671) recommends "measurement of the unobservables which create the endogeneity concerns in the first place." Therefore, we believe that the return policy endogeneity, caused primarily by retailer-level omitted variable bias, is best addressed through the control variable approach in our context. While the control variable approach is a less frequently used solution since collecting the omitted variables is a very time consuming and costly process (Ching et al., 2015, p.14), we undertake this task and are able to implement it with an extensive effort on variable construction.

4.3. Estimating the value of a full refund policy

We use fixed-effect OLS regression to quantify the value of a full refund policy. Specifically, given the binary nature of *ReturnPolicy*, its coefficient captures the dollar value that consumers assign to a full refund policy. That is, holding all else equal, the value increment from purchasing a product without refund to the same product with refund. Since we categorize our control variables into pre-defined groups, we add them to the variable specification one group at a time (see Table 8). Comparing Models (V1) and (V6), we see that the combined effect of all control variables is a reduction in the impact of a full refund policy by about \$0.8, or 12%, from \$6.5 to \$5.7. Next, we discuss the effects of specific control variables.

Among the time-related variables, the literature offers mixed insights regarding *Workday* and *Daytime* (e.g. Subramanian and Subramanyam, 2012; Lei, 2011; Cabral and Hortaçsu, 2010). For the products in our sample, the auctions that end during the day hours appear to register a higher price. *Month* has a negative effect, as expected, due to the relatively quick value depreciation of consumer electronics. Regarding the auction dynamics, the effects of all four variables are in the expected positive direction. On one hand, since a full refund policy will attract more bidders and more bids,[12] inclusion of *Bidders* and *Bids* in Model (V3) should decrease the effect size of *ReturnPolicy*. That is, the fraction of *ReturnPolicy* effect "transmitted" through Bidders and Bids is controlled for. On the other hand, since retailers offering a full refund policy tend to set a lower starting price for the auction,[13] inclusion of *StartPrice* should increase the effect size of *ReturnPolicy*. Overall, our estimate for the *ReturnPolicy* impact increases from Model (2) to (3) by more than \$1, suggesting a larger influence of *StartPrice*. Together, these show the importance of controlling for auction dynamic variables when estimating the value of a product or policy attribute. The price-determining bidder's characteristics, *BuyerExp*, *BidderFb*, and *BidAtSeller*, do not have significant direct effects on the auction price. Among the listing features, the three selling skill variables, *Images*, *DesLength,* and *TitleSkill*, all exert a significant positive impact on the auction price, as expected. Recall that ReturnFbRatio counts the positive return experiences from previous buyers' feedback. While this conveys a return-specific retailer reputation to the buyers, it might also remind some consumers about the possibility of needing to return the product, who otherwise tend not to think about this consequence. Interestingly, our results show that the latter effect appears to dominate as the coefficient for this term is negative but not significant. Further, *RevisedFb* registers a negative effect, which indicates that revisions to the feedbacks received by a retailer might remind customers of the risk of an online purchase (e.g. not receiving the item on time or receiving a broken item). Lastly, although *ShipCharge* is not expected to add value to a product, our result shows a positive effect at about \$0.4. This might be explained by some consumers considering it fair for the retailer to de-bundle the cost of shipping from the product's price.

We include two interaction terms in Model (V7) to tests Hypothesis LABEL:hyp:ship and LABEL:hyp:buyer. The interaction effect between ReturnPolicy and ShipCharge is negative but between ReturnPolicy and LogBuyerExp is positive.[14] Both are highly significant, supporting Hypothesis LABEL:hyp:ship and LABEL:-hyp:buyer. To further understand how the effect size of ReturnPolicy changes as a function of shipping charge and buyer's past auction participation, we construct two confidence band plots (a.k.a Johnson-Neyman plots) in Fig. 3. First, we observe that the shipping charge quickly erodes any positive impact of offering a full refund policy. Specifically, as *ShipCharge* moves from zero to \$15.4, the effect of *ReturnPolicy* decreases from around \$10 (or 2.5%, assuming a \$400 product price) to being statistically indifferent than zero. The mean effect size further decreases to zero when the *ShipCharge* = \$22.5. Thus, with a shipping cost of around 5% of the total purchase price (i.e. consider $\frac{20}{400} = 0.05$), the cost of not recovering the forward shipping charge when returning a product appears to dominate the risk mitigation benefits of full refund for the buyers. Second, within the range of *LogBuyerExp* that is commonly observed in the data (i.e. 0 to 5), the impact of full refund on the auction price exhibits a large variation, demonstrating strong heterogeneity of the perceived full refund policy value across buyers. Interestingly, those who rarely participate in online auctions seem not to value the full refund policy. In contrast, those who make frequent purchases assign a significantly higher value, over \$15 or 3.75%, to full refund.

To explore heterogeneity across products, we ran a product-level analysis using the specification of Model (6). The estimated full refund policy values for the five products are between 1% (GoPro Black) and 4% (Xbox with Kinect),[15] all of which are well below the 20–30% for catalog and in-store apparel products reported in the literature (Anderson et al., 2009; Heiman et al., 2015).

5. Robustness analysis

In this section, we present additional analyses to show the robustness of our previous results and discuss the case when buyers may bid below their valuation for a product.

5.1. Robustness checks for return policy driver analysis

In §3.3, we have discussed two methods to construct a sample of first time retailers. While our main analysis is focused on the "likely first-time retailer" sample, we present results from the "absolute first-time retailer" sample here.[16] For expositional brevity, we rerun the regressions in Model (D4), (D8), and (D13) and present the

[12] The correlations between ReturnPolicy and Bidders, and between ReturnPolicy and Bids, are 0.18 and 0.17.

[13] The correlation between ReturnPolicy and StartPrice is −0.21.

[14] We thank an anonymous reviewer for suggesting that non-paying buyers might in part account for this effect.

[15] Full regression results are available upon request.

[16] CommuRate has almost no variance in this smaller sample, and it is therefore excluded from this analysis.

Table 8
OLS regressions for the impact of full refund return policy on auction price ($N = 3139$).

	Model (V1)	Model (V2)	Model (V3)	Model (V4)	Model (V5)	Model (V6)	Model (V7)
ReturnPolicy	6.5*** (1.3)	5.9*** (1.2)	7.1*** (1.2)	7.1*** (1.2)	5.4*** (1.3)	5.7*** (1.4)	6.1** (2.1)
Workday		−0.7 (1.1)	−0.6 (1.1)	−0.6 (1.1)	−0.5 (1.1)	−0.5 (1.1)	−0.3 (1.1)
Daytime		1.9 (1.2)	2.1† (1.2)	2.1† (1.2)	2.6* (1.2)	2.2† (1.2)	2.2† (1.2)
Month		−3.6*** (0.4)	−3.5*** (0.3)	−3.4*** (0.5)	−3.1*** (0.5)	−2.9*** (0.5)	−2.8*** (0.5)
Bidders			1.1*** (0.2)	1.1*** (0.2)	1.2*** (0.2)	1.1*** (0.2)	1.2*** (0.2)
Bids			0.6*** (0.1)	0.6*** (0.1)	0.6*** (0.1)	0.6*** (0.1)	0.6*** (0.1)
AuctionDuration			0.6** (0.2)	0.6** (0.2)	0.4* (0.2)	0.3 (0.2)	0.3 (0.2)
StartingBid			0.1*** (0.01)	0.1*** (0.01)	0.1*** (0.01)	0.1*** (0.01)	0.1*** (0.01)
LogBuyerExp				0.01 (0.5)	−0.2 (0.5)	−0.1 (0.5)	−0.9† (0.5)
BidderFb				−1.8 (1.6)	−1.0 (1.6)	−1.0 (1.6)	−0.8 (1.6)
BidAtSeller				0.5 (1.6)	0.7 (1.6)	1.4 (1.6)	1.6 (1.6)
ShipCharge					0.4*** (0.1)	0.4*** (0.1)	0.5*** (0.1)
ShipService					−1.2 (1.1)	−2.2† (1.2)	−2.2† (1.2)
Images					1.0*** (0.2)	1.0*** (0.2)	1.1*** (0.2)
DesLength					2.1*** (0.5)	2.3*** (0.5)	2.3*** (0.5)
TitleSkill					2.5** (0.8)	2.0* (0.8)	1.9* (0.8)
SellerYear						0.4*** (0.1)	0.4*** (0.1)
Store						−2.2 (2.0)	−1.5 (2.0)
LogPosiFb12						0.4 (0.5)	0.4 (0.5)
LogNegaFb12						0.5 (0.9)	0.6 (0.9)
NumElecFb						−0.03 (0.02)	−0.03† (0.02)
CommuRate						0.3 (0.3)	0.3 (0.3)
ReturnFbRatio						−14.2 (9.6)	−14.3 (9.6)
RevisedFb						−2.1* (0.8)	−1.6† (0.9)
ReturnPolicy_X_ShipCharge							−0.4*** (0.1)
ReturnPolicy_X_LogBuyerExp							3.0** (1.0)
Product FE	Included	Included	Included	Included	Included	Included	Included
Constant	254.2*** (2.2)	269.8*** (2.9)	232.0*** (3.7)	232.8*** (4.7)	209.7*** (5.9)	204.3*** (6.1)	203.3*** (6.0)
Adjusted R^2	0.68	0.69	0.72	0.72	0.73	0.73	0.73

†$p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Standard error in parentheses. Prefix “V” stands for value analysis.

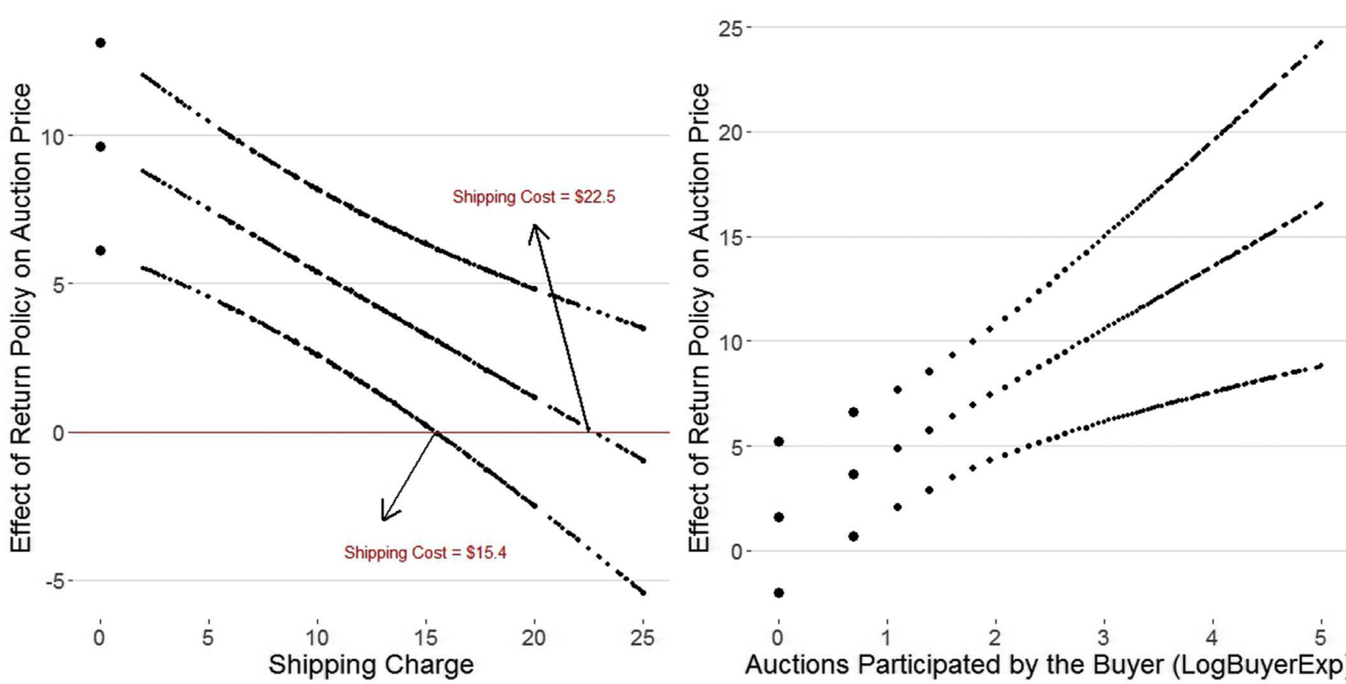

Fig. 3. Confidence Band Plots for the Interaction Effects.
*Note.*The three curves in each plot represent the upper bound, mean, and lower bound of *ReturnPolicy's* effect on Price. The left plot assumes *BuyerExp* at its mean and the right plot assumes *ShipCharge* at its mean. *ShipCharge* > 25 and BuyerExp > 5 are truncated to make the plots more readable. Dots on the three curves are the actual data points in the sample. Size of the dots represent observations with overlapping values. For example, there are many observations with *ShipCharge*= 0. Thus, our plots could be considered as an “empirical version” of the popular confidence band plot (Bauer and Curran, 2005).

results in Table 9 in Model (DR1), (DR2), and (DR3), respectively (see Appendix D for variable summary statistics). For competitive intensity variables, we find our previous conclusion holds for all but *LowPriceDay*, which registers a marginally significant impact on *ReturnPolicy*. Therefore, H1a again receives little support in this alternative sample. Since the impact of *LowPriceDay* signals that the reverse causal relationship from past price to current return policy choice, although being weak, might still exist, we include it as a

Table 9
Robustness: Return policy drivers in the absolute first time seller sample.

Model (DR1)		Model (DR2)		Model (DR3)	
NumListLive	0.016 (0.012)	NumListDay	−0.019 (0.031)	SellerYear	−1.146 (1.328)
AvgPriceLive	−0.005 (0.025)	AvgPriceDay	−0.003 (0.010)	Store	1.623* (0.756)
LowPriceLive	0.003 (0.007)	LowPriceDay	−0.01† (0.005)	LogTotalFb12	0.208 (0.141)
PctFullLive	−0.027 (2.299)	PctFullDay	0.397 (0.808)	NumElecFb	0.614† (0.327)
				ReturnFbRatio	2.180* (1.048)
Product FE	Included	Product FE	Included	Product FE	Included
Constant	2.747 (6.610)	Constant	5.506* (2.612)	Constant	0.942 (0.915)
N	250	N	321	N	324
LL	−142.607	LL	−179.297	LL	−171.422
LR Test	2.411 (4)	LR Test	0.264 (4)	LR Test	26.77*** (5)

†$p < 0.1$, *$p < 0.05$, ***$p < 0.001$. Prefix "DR" stands for robustness check for driver analysis. The "LR Test" rows show likelihood ratio test results (χ^2 statistics) for the 4 variables in Model (DR1), the 4 variables in Model (DR2), and the 5 variables in Model (DR3), with corresponding degrees of freedom in parentheses.

Table 10
Robustness: Alternative Specifications for Return Policy Driver Analysis.

	Model (DR5)	Model (DR6)	Model (DR7)
SellerYear	−0.031** (0.011)	−0.046** (0.014)	−0.031** (0.011)
Store	1.660*** (0.187)	1.711*** (0.185)	1.708*** (0.187)
LogTotalFb12			0.081† (0.043)
LogTotalFb6	0.130** (0.046)		
LogFbScore		0.084* (0.040)	
NumElecFb	0.015* (0.007)	0.017* (0.008)	0.017* (0.008)
CommuRate	2.297*** (0.560)	2.359*** (0.562)	2.420*** (0.574)
ReturnFbRatio	0.098** (0.033)	0.121*** (0.031)	0.116*** (0.033)
CommuFbRatio			−0.525 (0.492)
Product FE	included	included	included
Constant	−2.002*** (0.137)	−2.022*** (0.148)	−1.971*** (0.143)
LL	−1138.36	−1140.15	−1139.94
LR Test	8.008*	4.422*	1.219

†$p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Model numbering continues from Table 9. The "LR Test" row shows likelihood ratio test results (χ^2 statistics) for LogTotalFb6, LogFbScore, and CommuFbRatio. For example, LR Test for Model (DR5) compares its likelihood with that of its nested model (i.e. removing LogTotalFb6.), yielding a χ^2 statistic of 8.008, significant at 0.05 level.

control variable in a robustness check for the return policy value analysis to further rule out the potential influence of reverse causality. Model (DR3) demonstrates that the impact of product salvage value and retailer reputation variables are by and large consistent with what is observed previously, despite a weaker statistical significance (expected from a much smaller sample).

Next, using Model (D13) in Table 7 as a baseline, we carry out additional regressions to test the robustness of our finding that product salvage value and retailer quality are valid drivers of a retailer's choice of offering a return policy (within the likely first time retailer sample). First, we use two alternative measures to capture the overall sales volume of a seller, *LogTotalFb6* and *LogFbScore*, in Models (DR5) and (DR6), both showing a significant positive effect (See Table 10). Thus, these additional analyses further strengthen the evidence for salvage value as a return policy driver, given that sales volume is a strong proxy for salvage value. Second, we test for the effect of the return-related feedback text further by adding a new variable, *CommuFbRatio*, which captures the buyers' positive experience of communicating with the seller. This variable is correlated with *ReturnFbRatio* and might also affect a retailer's return policy choice. However, Model (DR7) shows that CommuFbRatio does not explain return policy choice beyond *ReturnFbRatio*.

5.2. Robustness checks for full refund policy value analysis

We perform a series of robustness checks for the full refund policy value analysis, starting with alternative specifications based on our focal variables (Panel A in Table 11). Previous studies (e.g. Cabral and Hortaçsu, 2010; Lei, 2011) have used a log-transformed version of the eBay auction price as the dependent variable, arguing that the left-truncated log-normal distribution does not draw on negative values and hence better captures consumers' product valuation. We use (untransformed) total price in our main analysis since the estimated effects have a direct dollar value interpretation and the products in our sample are at a price level that makes a negative estimated price extremely unlikely. Nevertheless, we perform a robustness check for log-transformed price in Model (VR1), yielding qualitatively identical results. Since the log-transformed price entails coefficients that can be interpreted as (approximately) the percent change in price, we observe that consumers pay 1.5% higher when a full refund policy is attached. We next remove the shipping cost entirely from the model, alleviating the concern that the full refund effect is in part due to its correlation with *ShipCharge*, and *ShipCharge* enters the model in a non-linear fashion. Specifically, we use product price (not total price) as the dependent variable in Model (VR2) and leave out *ShipCharge* from the independent variables. In order to make a direct comparison with the main analysis, we estimate only the main effect of offering a full refund policy, yielding comparable results to Model (V6) in Table 8. We then estimate Model (VR3) using only the free shipping observations, where *ReturnPolicy's* effect is \$6.975, which is \$1.22 higher than the estimate from Model (V6) in the main analysis. This demonstrates that the estimated impact of offering a full refund policy, conditional on free shipping, is higher (removing the parametric assumption that a positive shipping charge linearly decreases a return policy's effect on price). In Models (VR4) and (VR5), we remove the top 3% of *ShipCharge* and *BuyerExp* for each product due to the large values observed in Fig. 2. In this case, our results remain similar to those from the main analysis.

Next, we turn to alternative model specifications based on retailer characteristics (Panel B in Table 11). First, we use alternative variables to capture a retailer's feedback reputation, which our main analysis reveals as an important return policy driver. In Models (VR6)-(VR8), *LogTotalFb12*, *LogTotalFb6*, and *LogFbScore*[17] replace the positive and negative feedback variables (*LogPosiFb12* and *LogNegaFb12*), all producing similar results as in the main model. We then construct a dummy variable to capture a retailer's sales volume that is specific to the auctions in our sample. Specifically, we contrast retailers with 10 or more listings (19 such retailers) with smaller retailers. This addresses the concern that large retailers are more likely to offer both a lenient return policy and register a higher price. Model (VR9) shows that the inclusion of this

[17] These variables are chosen to mimic our specifications in the return policy driver analysis.

Table 11
Robustness: Alternative specifications for full refund value analysis.

	Panel A: alternative specifications based on focal variables				
	Model (VR1) Logged DV	**Model (VR2) Product price**	**Model (VR3) Free shipping only**	**Model (VR4) Remove large ShipCharge**	**Model (VR5) Remove large LogBuyerExp**
ReturnPolicy	0.015** (0.006)	6.635*** (1.458)	6.975** (2.270)	5.192* (2.130)	5.584* (2.169)
ReturnPolicy_X_ShipCharge	−0.001*** (0.0003)			−0.313* (0.124)	−0.441*** (0.117)
ReturnPolicy_X_LogBuyerExp	0.008** (0.003)			2.844** (0.975)	3.149** (1.177)
Observations	3139	3139	1042	3060	3043
Adjusted R^2	0.756	0.727	0.758	0.733	0.734
	Panel B: alternative specifications based on seller characteristics				
	Model (VR6) Total feedback	**Model (VR7) 6 month total feedback**	**Model (VR8) Feedback score**	**Model (VR9) Large vs small seller**	**Model (VR10) Seller-cluster robust std. err.**
ReturnPolicy	5.994** (2.088)	6.019** (2.087)	5.989** (2.087)	6.181** (2.098)	6.085* (2.636)
LogPosiFb12				0.348 (0.486)	0.353 (0.534)
LogNegaFb12				0.458 (0.866)	0.551 (1.030)
LogFb12	0.519 (0.405)				
LogFb6		0.500 (0.426)			
LogFbScore			0.666† (0.369)		
BigRetailer				1.238 (1.848)	
ReturnPolicy_X_ShipCharge	−0.418*** (0.114)	−0.419*** (0.114)	−0.423*** (0.114)	−0.428*** (0.114)	−0.424* (0.165)
ReturnPolicy_X_LogBuyerExp	3.034** (0.964)	3.037** (0.964)	2.973** (0.965)	2.994** (0.967)	2.985* (1.290)
Observations	3139	3139	3139	3139	3139
Adjusted R^2	0.73	0.73	0.731	0.73	0.73

†$p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Standard errors in parentheses. Control variable specification is the same as in Model (V7) in Table 8. Full table is in Appendix F. Prefix "VR" stands for robustness check for value analysis.

retailer size variable has only a minor impact on the estimation results. Finally, Model (VR10) reruns Model (V7) in the main analysis with robust standard errors clustered at the retailers. Once again, the results are similar to those from the main analysis.

Lastly, we present two endogeneity-related robustness checks. Since a retailer tends to stick to a return policy choice once decided, we have concluded that the effort for addressing return policy endogeneity should be focused at the retailer-level, and we only included the retailers who have not changed their return policy in the main analysis. In the first robustness check, we add back all the auctions hosted by return policy changers, which increases sample size from 3139 to 3192, and rerun regressions using the specifications in Model (V6) and (V7). As shown in Table 12, for both the average effect of *ReturnPolicy*, Model (VR11), and its interactions with *ShipCharge* and *BuyerExp*, Model (VR12), we observe strong consistency with the main analysis. Thus, as we expected, although the possible auction-level endogeneity problem is neglected, its impact is minimal, if any. Furthermore, since *LowPriceDay* is a marginally significant driver of *ReturnPolicy* in the absolute first time seller sample, we add *LowPriceDay* to our return policy value regression to further rule out the potential reverse causality impact, Model (VR13) and (VR14). Again, for both the average effect of *ReturnPolicy* and its interactions with *ShipCharge* and *BuyerExp*, we observe strong consistency with the main analysis.

5.3. Interpreting bid price as product value

Given the similarity between the second-price English auction and the auction format on eBay, many prior studies (e.g. Bajari and Hortaçsu, 2003; Cabral and Hortaçsu, 2010; Subramanian and Subramanyam, 2012) make the implicit assumption that "bid = value." That is, a buyer will bid his/her valuation of the product – an established theoretical result for rational bidders. Since auction prices directly result from top bids, this assumption entails that the coefficients in our previous analysis can be interpreted as the impact on consumers' product valuation (instead of merely the final auction price). It is especially appealing to have such an interpretation for the return policy effect. However, the "bid = value" assumption has been challenged by Zeithammer and Adams (2010), who show using eBay data that not all bidders bid in a "sealed" fashion (i.e. bid their true valuation). Rather, some bidders bid in a "reactive" fashion such that they will initially bid only a fraction of their valuation and raise their bid gradually whenever they are outbid (Zeithammer and Adams, 2010, p.966), suggesting that the final bids of reactive top bidders might be smaller than their true product valuation. Therefore, if we directly regress auction price on return policy, the identified effect might not represent the true value of a full refund policy due to the potential bias in the dependent variable.[18] Following their insights, we tease out a subset of auctions from our data set where the second highest bidder is either very unlikely to be a reactive bidder or is a reactive bidder who has revealed his/her true product value in their last bid. As a result, the "bid = value" assumption should continue to hold for the final bid from the second highest bidder. We present the details on the construction and analysis of this "bid = value" sample in Appendix E.

The regression estimates from this sub-sample are presented in (Table 13). The dependent variable (*SecondPrice*) is calculated as the sum of the second highest bid and the shipping charge (i.e., replacing the auction price with the second highest bid in the main analysis). Using the specifications of the last two models in Table 8, we rerun these regressions on the "bid = value" sample. As shown in Model (VR15) in Table 13, the average full refund policy impact (without interactions) is $3.85, slightly than the estimate from the whole sample of $5.7. That is, after mitigating the influence of reactive bidding, we see that the gap for auction prices between auctions with and without a full refund become narrower. However, the two interaction effects in Model (VR16) have similar sizes

[18] In a recent study, Hui et al. (2016) assume that buyers' willingness-to-pay is their bid scaled by a factor, which is constant across several groups of eBay auctions facing different reputation and regulation. Following this assumption, the full refund impact expressed as a percentage of auction price will have no bias. For example, the average full refund impact is estimated to be $5.7 (Model (V6) in Table 8) and average auction price in the sample is $367.9 (Table 4), indicating that full refund is worth 1.5% of the product price.

Table 12
Robustness: Additional endogeneity-related checks.

	Model (VR11)	Model (VR12)	Model (VR13)	Model (VR14)
ReturnPolicy	5.697*** (1.389)	6.554** (2.031)	6.325*** (1.534)	5.772* (2.266)
LowPriceDay			−0.016 (0.015)	−0.013 (0.015)
ReturnPolicy_X_ShipCharge		−0.440*** (0.111)		−0.401** (0.125)
ReturnPolicy_X_LogBidItems		2.729** (0.955)		3.632*** (1.045)
Observations	3192	3192	2882	2882
Adjusted R^2	0.729	0.731	0.659	0.662

$^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$. Standard error in parentheses. Control variable specification is the same as in Model (V7) in Table 8. Full table is in Appendix F. Model numbering continue from Table 11.

Table 13
Robustness: Impact of return policy on bid price in the "Bid=Value" sample (N=1512).

	Mode (VR15)	Mode (VR16)
ReturnPolicy	3.850* (1.960)	4.971† (2.719)
ReturnPolicy_X_ShipCharge		−0.412** (0.144)
ReturnPolicy_X_LogBuyerExp		2.450* (1.178)
Adjusted R^2	0.767	0.769

$^{\dagger}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$. Standard errors in parentheses. Dependent variable is calculated as the sum of the second highest bid and the shipping charge. Control variable specification is the same as in Model (V7) in Table 8. Full table is in Appendix F. Model numbering continue from Table 12.

to the estimates from the main analysis. Specifically, a shipping charge erodes the positive effect of full refund policy at almost the same rate. Buyers' past bidding frequency, *LogBuyerExp*, increases the full refund effect at a slightly smaller rate than the full sample estimate (i.e. 2.45 vs 3.0). In general, the control variable effects are also qualitatively consistent.

To summarize, our additional analyses presented in this section shows that while the reactive bidding behavior has been demonstrated to contaminate the interpretation of auction price as bidders' product value, it appears to exert only a small influence on our regression estimates for the impact of a full refund policy.

6. Discussion and conclusion

Motivated by the inconsistency between the theory (which often advocates for partial refunds) and practice (where full refunds are prevalent) of return policies, we analyze both the value and the potential drivers of a retailer offering a full refund policy using a data set collected from eBay. We show that, among the three theoretical drivers, retailers on eBay consider product salvage value and their own reputation/quality, but not the competitive intensity when setting their return policies. Since theory and practice are mostly aligned on the input parameters for setting the "right" return policy, it adds to the urgency and importance of understanding return policy benefits for different products and using different methods. Our analysis of full refund policy value contributes from two aspects. Surprisingly, we find that the impact of offering a full refund policy on a product's final auction price is relatively small, providing new guidance on the value that consumers actually place on full refunds. In addition, this value quickly erodes when the retailer charges a positive shipping fee, or when it is faced with buyers who have little online purchase experience. Overall, our empirical evidence cautions against an overly optimistic view of offering generous return policies, especially for consumer electronics.

In the following subsections, we discuss the specific managerial and theoretical implications offered by these results, followed by the limitations of our study and future research directions.

6.1. Managerial implications

Many online retailers, like eBay sellers, are SMEs, which are less confined by the need to have a uniform return policy across their assortment. For large retailers such as BestBuy, maintaining the same return policy imposes less confusion on consumers and also makes it easy to communicate. However, for retailers on e-marketplaces such as eBay, products are sold through listings, making inconsistency of return policy within a retailer less of a concern. As a result, our estimates of the full refund policy value are particularly relevant for these smaller retailers who may consider "switching" their full refund policies on or off, but lack guidance on the appropriate changes in the price premium.

Additional insights are provided by contrasting our estimates for consumer electronics with those from the literature for apparel products. As revealed by our empirical analysis, the value of full refund in our sample is, on average, less than 3% of the total product value (i.e., consider a $10 full refund policy value for a $350 Xbox). This is substantially lower than the 20–30% for catalog and in-store apparel products estimated by Anderson et al. (2009) and Heiman et al. (2015). This difference may be explained by the varied degree of word-of-mouth information available for the two product categories. Unlike the apparel sales, each product included in our sample has its own review page on eBay. Consumers could also augment this information by searching on other websites such as Amazon and CNET. As a result, much of the uncertainty regarding product fit may potentially be resolved before purchase, which limits the value of a full refund policy. In comparison, word-of-mouth information for apparel products is much less available, given their wide variety. Furthermore, it is likely to be more difficult for consumers to use word-of-mouth information to determine the individual fit of an apparel product.

Toktay et al. (2003) categorizes return management efforts into active and passive strategies. In practice, the former includes buyer assistance programs (Ferguson et al., 2006; Ofek et al., 2011) and virtual fitting technologies (Gallino and Moreno, 2015). The latter includes operational models of reverse supply chains (Guide et al., 2006) and returns forecasting (Shang et al., 2016). However, the most influential active strategy, adjusting the return policy, while being researched extensively in the analytical literature, is rarely practiced by retailers. Our results regarding the relatively small value of full refund policies for consumer electronics (around 3%) should motivate retailers to re-examine whether their generous refund policies are indeed justified, especially given the reported return rates of 12% (National Retail Federation, 2016; Ng and Stevens, 2015). One indication that retailers are recognizing that their policies may be too lenient is the recent trend of tightening the time window for returns. Well publicized examples include

Costco, which ended its lifetime return policy on consumer electronics (Hudson, 2007), and REI's decision to shorten its return time window from unlimited to one year (Grind, 2013).

Our analysis also shows the importance of controlling for relevant factors when estimating the impact of a full refund. For example, the "naïve" specification in Model (V1) of Table 8, where no controls are included, produces a full refund impact of \$6.5. In contrast, when the full set of controls are included in Model (6), its impact is estimated at \$5.7, or a 12% decrease, demonstrating the risk of overstating the value of a full refund policy.

Finally, our results suggest that forward shipping charges have implications for both the costs and benefits of offering a full refund. On one hand, a lower forward shipping fee increases the value of the full refund policy to consumers. On the other hand, the retailer may incur more costs if customers are more likely to return products when shipping costs are low. In addition, while the actual forward shipping charge incurred by a retailer is primarily driven by its agreement with the shipping carrier, the shipping fee it charges to the consumers is at its own discretion. Thus, the results from our return policy benefit analysis could be used by retailers to help determine the optimal shipping charge to offer consumers.

6.2. Theoretical implications

Our work also has several theoretical implications. We describe them in turn. In light of the reported high return rates, often greater than 12% for consumer electronics sold online (National Retail Federation, 2016; Ng and Stevens, 2015), our finding of a small value of a full refund policy (3%) suggests that consumers' subjective return probability (mentally estimated before purchase) is likely to present a substantial downward bias as compared to the actual. Recent studies applying Prospect Theory to consumer returns have emphasized the roles of loss aversion (Heiman et al., 2015) and reference dependence (Shulman et al., 2015). The former usually leads to a higher value of a full refund to consumers. Our study complements this literature by highlighting the potential role of subjective return probability, the third behavioral piece in Prospect Theory. As a result, it is important for future behavioral studies to take a holistic view, similar to the approach in Jindal (2014), for studying how subjective probability, loss aversion, and reference dependence together affect consumer return policy preference.

It is surprising that charging for shipping decreases the value of full refund policy at such a rapid rate. With a shipping charge of around \$20, the value of a full refund policy for a \$400 item could be close to zero (Fig. 3). Since a shipping charge is considered as a "latent" restocking fee, the detrimental effect of a true restocking fee might even be higher. Practically, this might offer a reason to justify the popularity of retailers not charging restocking fees. From a theoretical standpoint, this might be indicative of a "special zero effect" for the restocking fee, which is hard to test in our data due to the very small number of retailers that charge restocking fees. Shampanier et al. (2007) show that consumer utility makes a discontinuous dip when the price increases from zero to as little as one cent. Our results motivate a similar investigation for the zero restocking fee effect in the returns context. That is, a consumer might react much more negatively to an increase in the restocking fee from 0 (full refund) to x than she would to an equivalent increase from x to 2*x*.

Given the small full refund policy value and potentially large negative impact from charging a restocking fee, it appears to make sense for retailers to choose one of two extremes – either not charge a restocking fee (full refund) or not accept returns at all (no refund). A number of analytical models also adopt this binary assumption of return policy choice (e.g. Che, 1996; McWilliams, 2012).

6.3. Limitations and future research

There are several limitations worth noting about our study. First, our analysis of the full refund value focuses on the increase in consumers' product valuation, which can be considered as an immediate or short-term benefit. Altug and Aydinliyim (2016) suggest that lenient return policies might stimulate aggregate demand or market size. However, the size of such long-term benefit remains empirically unclear. A stream of literature on consumer returns focuses on the repurchase behavior of frequent returners. For example, Griffis et al. (2012) demonstrate in online book retailing that, consumers who returned in the past tend to order more frequently, include more items in an order, and buy more expensive items than those who never returned. This "more returns today, more purchases tomorrow" view is shared by Petersen and Kumar (2009). Mollenkopf et al. (2007) also illustrate a similar positive effect on consumers' perceived loyalty to the retailer after making a return. The existence and magnitude of a similar impact on the repurchase behavior due to the leniency of a return policy is an interesting area of future research.

Second, while the eBay platform allows us to observe the same products, with and without return policies, it also confines us to a retailer pool made up mostly of SMEs and a buyer pool made up by relatively patient and cost-cautious customers. We speculate that full refund policy value estimates from this retailer pool might be higher than that for established retailers, since consumers shopping from "less-known" retailers may feel a stronger need to be protected by a return policy. Beyond shipping charges, returns made through the online and physical channels also exhibit differences in terms of "hassle costs," which include packaging and return shipping costs for the former and travel cost for the latter. Since it is not clear which channel has a larger hassle cost, some caution is needed for any attempt to infer our estimates for full refund policy value to products sold at a physical store.

Last, since our data has limited variation in the return time window and partial restocking fee, we were unable to quantify their values in this paper. We leave it to future research to examine the time dimension of a retail return policy, as well as contrasting the impact of an explicit restocking fee as opposed to a non-refundable shipping charge.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jom.2017.07.001.

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