Charity as a substitute for reputation: Evidence from an online marketplace*

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Abstract

Consumers respond positively to products tied to charity, particularly from sellers that are relatively new and hence have limited alternative means for assuring quality. We establish this result using data from a diverse group of eBay sellers who "experiment" with charity by varying the presence of a donation in a set of otherwise matched product listings. Most of charity's benefits accrue to sellers without extensive eBay histories. Consistent with charity serving as a quality signal, we find fewer customer complaints among charity-intensive sellers.

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1. Introduction

In markets with unobserved quality, sellers benefit from credible signals of trustworthiness. If the outcomes of past transactions are widely observable, sellers may build trust through reputation. A seller that has consistently delivered on his end of the contract in the past reveals not only sufficient competence, but also that he possesses a low discount rate or a preference for honesty that makes shirking unattractive. In these markets with asymmetric information, sellers without observable track-records of performance benefit from alternative signals that may substitute for reputation and speed the rate of reputational development. One common suggestion from the economics literature is "money burning" through advertising, introductory offers, or other upfront costs that are valuable only to high-quality sellers in the long run (Milgrom and Roberts 1986).

In this paper, we examine empirically charitable giving as a mechanism for signaling seller quality. To describe how this can occur in equilibrium, we develop a simple model based on the assumption that less opportunistic owners or managers are also those who derive greater utility from contributions to public goods. The model describes conditions under which (purely self-interested) consumers have a higher willingness-to-pay for purchases from charitable sellers, and illustrates why this "charity premium" declines as alternative indicators of trustworthiness – such as a more extensive public performance track-record – become available. The model guides our empirical analysis of the differences in outcomes between charity and non-charity items, and it highlights the underlying assumptions that are sufficient for donations to serve as quality signals.

We examine these predictions using a novel dataset comprised of more than 160,000 eBay listings that are precisely matched into groups by seller, title, and start price but vary in the fraction of proceeds donated to charity, from zero to 100%. By comparing auction outcomes within each matched group, we estimate a charity premium that varies across sellers with different verifiable feedback (i.e. experience) levels. The eBay marketplace provides an ideal testing ground for our theory. Trade in this market is vulnerable to service problems and seller misrepresentation, and public records of prior transactions are used as assurances of trustworthiness (Houser and Wooders 2006, Resnick et al. 2006, Cabral and Hortacsu 2010).

Our empirical results indicate that young and inexperienced sellers derive greater benefit from tying products to charitable donations, consistent with charity providing an alternative form of quality assurance. We further explore the signaling hypothesis by examining differences in buyer-initiated disputes with sellers that vary in their level of charitability, and also by examining whether the charity premium we estimate is consistent with the separating conditions of our theoretical model. We find that buyers are less likely to be dissatisfied when purchasing from more charitable sellers, and that the charity premiums we estimate are positive, yet too small to entice low-quality sellers to link their product sales to donations.

The charity auctions we study are made through eBay's Giving Works (GW) program, which allows sellers to direct 10% or more of an auction's proceeds to a charity of their choice. We utilize a new dataset that provides the universe of GW auctions between January 2004 and March 2008. In any quarter when a seller had at least one charity auction, we additionally observe all non-charity auctions by the seller in that quarter. In many cases we observe sellers offering several units of identically described products using a mix of charity and non-charity auctions. We focus our attention on a sample of 22,610 groups of auction listings in which a single seller offers a number of listings that all share the same title, subtitle, and start price, but differ in the fraction of the final proceeds that are donated to charity. These groups represent quasi-experiments performed by 5,015 eBay sellers from which we can infer the impact of charitable giving on consumer demand. Our focus on this carefully selected sample of quasi-experiments allows us to interpret differences in consumers' responses as resulting from the presence of the donation itself rather than unobserved seller heterogeneity.

We present four main empirical results, which together support the hypothesis that charity can serve as a signal of seller quality on eBay. First, we find that linking products with charitable donations leads to higher sale probabilities and prices across the entire sample of quasi-experiments. Because it reduces their net cost of donating, this premium makes charity ties an efficient way for sellers to make donations.

Second, we find that there is considerable heterogeneity in benefits across sellers with different levels of experience, consistent with charity conveying information about expected quality. Premiums from GW in sale probability and price are highest for those with the least feedback. For sellers in the lowest feedback quartile, GW auctions are associated with a 12 percentage point higher sale probability and 4 percent higher prices when 10% is donated, and as much as a 54 percentage point increase in sale probability and 25% higher prices for 100% charity auctions. For sellers in the highest feedback quartile, the effects of charity tie-ins are less than one fourth as large. This relationship between GW impact and seller feedback is robust to many different specifications that seek to test alternative explanations.

Third, the combined effects of increased sale probability and price are not so large as to tempt low-quality or opportunistic sellers to link products with charitable donations. Assuming that such opportunistic sellers receive no utility from charitable donations, the separating condition in a signaling model requires that the charity premium not "pay for itself." The magnitudes of our estimates suggest that GW auctions do not yield benefits that compensate for the revenue that goes to the charity, even for low feedback sellers.

Fourth, we use data on customer complaints to confirm that more charitable sellers offer higher quality service, as we conjecture in our theoretical model. Although all sellers in our sample have offered at least one GW listing, considerable variation exists in the fraction of listings a seller has tied to donations during her eBay history. Sellers who tie a greater fraction of their listings to donations – i.e., those who are more committed to charity – receive significantly fewer complaints from buyers.

Our work contributes most directly to the empirical literature on quality signaling under asymmetric information. In product markets, this empirical literature has examined the role of advertising (Thomas et al. 1998, Horstmann and MacDonald 2003), quality claims (Jin and Kato 2006), warrantees (Boulding and Kirmani 1993, Roberts 2010, Choi and Ishii 2010) and voluntary information disclosures (Lewis 2011) in signaling quality. Empirical studies on signaling firm-level attributes have investigated dividends (Bernheim and Wantz 1995; Bernheim and Redding 2001), alliances (Nicholson et al. 2005), and management-quality certification (Terlaak and King 2006). To the best of our knowledge, our paper is the first in this literature to demonstrate that the signaling mechanism of interest both affects prices in the marketplace and also satisfies the conditions for a separating equilibrium.

This paper is also connected to an emerging stream of empirical research that studies the impact of charity and other socially responsible practices on consumers' willingness to pay. Casadesus-Masanell, Crooke, Reinhardt, and Vasisth (2009) study Patagonia's introduction of organic cotton to its clothing products. In addition, a set of working papers examines how consumer demand is affected by labels indicating production according to ethical or fair trade standards (Haismueller, Hiscox, and Sequeira 2011; Hiscox, Broukim, Litwin, and Woloski 2011; Hiscox, Broukim, and Litwin 2011). These studies report significant effects of socially responsible practices on willingness to pay, but are not able to isolate the independent effects of corporate citizenship, product promotion, and quality signals. Elfenbein and McManus (2010a) investigate the relationship between donations and willingness-to-pay by estimating the price premium associated with Giving Works sales on eBay using a hand-matched dataset of identical items sold in GW and non-GW auctions. In contrast to this earlier work, the sample we construct for this paper provides better identification of a charity premium across a much wider set of products and enables us to study sale probabilities as well as prices. Critically, these data allow us to examine how the charity premium varies as a function of seller feedback and other attributes. More broadly, they enable us to be the first to demonstrate directly that the economic benefits of for-profit enterprises' charitable donations can depend systematically on their characteristics.

2. Illustrative model

We construct a simple model of equilibrium behavior in which charitable donations raise prices by signaling quality, and the price premium associated with donations declines as sellers develop reputations. Our central assumption is a positive correlation between a seller's utility from charitable giving and his disutility from behaving opportunistically towards consumers.[1] Unlike most prior work that examines corporate citizenship as a mechanism for product differentiation (Baron 2001, Bagnoli and Watts 2003) consumers in our model have no direct taste for charity. Our model is meant primarily for illustrative purposes, so we simplify the structure of preferences to ease exposition.

We assume that sellers are costlessly endowed with one good to sell in each of two periods, which occur in rapid succession so there is no discounting. Any consumer who obtains the good in perfect working condition receives gross utility v. To ensure that a buyer receives v, the seller pays c to undertake a quality assurance step that the buyer cannot observe in advance. This may be interpreted as ascertaining the product's provenance, care in handling and shipping, or repairing flaws or damage to the item. If the seller does not spend c, the product fails with probability γ, in which case the consumer receives zero utility. Consumers may not receive refunds for defective products, and sellers cannot credibly announce whether they have assured a product's quality.

[1] This assumption is embedded in some prior work. Siegel and Vitaliano (2007) discuss how such a correlation could facilitate trade in a market with experience goods. Fisman et al. (2006) explicitly model how the correlation can lead to an equilibrium where charity separates high-quality sellers from low-quality, and they explore the market structure implications.

Once a transaction is completed, the product's quality is observed by all agents. Thus, sellers in the second period will have an observable history, and hence "reputation," that is related to their first-period quality assurance actions. Product failure reveals perfectly that the seller neglected to spend *c*, but high quality does not clearly indicate seller effort. Consistent with eBay practices in reporting charity activity (see the discussion in Section 3), we assume that first-period donations are observed by first-period consumers before buying the good, but not by second period consumers, who can observe second-period donations only.

Sellers vary in their preferences for assuring quality and for charity. We make the extreme assumption that "good" (G) sellers who derive utility from charitable contributions *always* spend *c* to ensure product quality. We contrast this with "non-charity" sellers who do not receive utility from charitable donations. Of these, some proportion α will verify quality only when doing so is financially beneficial, while the remaining fraction $(1-\alpha)$ receive high disutility from deceiving customers and thus always spend *c*. The non-charity sellers with pure financial motivation are called "opportunistic" (O), while the non-charity sellers who always spend *c* are called "ethical" (E).

Sellers may bundle a fixed donation *d* with the sale of their products. The cost of this donation (relative to donating separately) is equal to $(1-\theta)d$, where $0 < \theta < 1$ for charity minded sellers and $\theta = 0$ for non-charity sellers.[2] We assume that θ is identical across all charity sellers. In all, a seller's period payoff, π_t, equals the price received, *p*, minus any

[2] As will be clear from the ensuing discussion, none of the results of the model are dependent on the functional form of this parameter; thus we choose a simple linear function.

quality assurance and donation costs incurred. The price itself is determined in equilibrium.

Consumers maximize expected utility and shop across sellers who vary in their observable reputations and current donation pledges. In equilibrium, consumers' expected utility from each seller is equal.[3] It is sufficient for our purposes to focus on equating consumers' benefits conditional on comparing sellers with the same experience level; this provides the relevant differences between the various prices in the market.

We now describe the conditions on model parameters that sustain a two-period separating equilibrium where charitable donations serve as a credible signal of quality verification.[4] Assuming that separation occurred in the first period, a fraction γ of type O sellers will have been revealed and carry a negative public feedback score into the second period. The proportion of good feedback (non-charity) sellers who are opportunistic but remain undetected is thus:

$$\alpha_2 = \alpha(1-\gamma)/(1-\gamma\alpha) < \alpha. \tag{1}$$

That is, the fraction of undetected O types will decrease in period 2, as first-period product failures reveal some opportunistic sellers. Since charity history is not known by consumers in period 2, products of reputable sellers (i.e., those without negative feedback) in this period are characterized by two prices: p_2^d, if the product is bundled with the donation and p_2^{nd}, if there is no donation.

The relationship between charity and non-charity prices of (positively) experienced

3 We abstract away from describing the precise price-setting mechanism.

4 A pooling equilibrium trivially exists. If consumers do not associate charity with higher quality, no seller will choose to donate.

sellers comes from equating consumers' expected utility from the two options: $v - p_2^d = (1 - \alpha_2\gamma)v - p_2^{nd}$. That is, the value from buying a non-charity item is weighted by the probability of encountering an opportunistic seller, and a further probability that the seller's negligence results in a bad product. Simplifying this condition yields the charity premium:

$$p_2^d - p_2^{nd} = \gamma\alpha_2 v. \qquad (2)$$

For second period separation between G and E sellers, the premium must be sufficient to motivate G sellers to bundle donations with their sales, i.e., $p_2^d - p_2^{nd} > (1-\theta)d$. Similarly, it cannot be so great as to induce non-charity sellers E and O to copy charity sellers by bundling products with donations, i.e., $p_2^d - p_2^{nd} < d$.

These inequalities show that the separating charity premium cannot be so large as to pay for itself, yet needs to be big enough to cover any utility cost to charity sellers from bundling. Combining these constraints on $p_2^d - p_2^{nd}$, we obtain the separating conditions in a single expression as a function of basic parameters:

$$(1-\theta)d < \gamma\alpha_2 v < d \qquad (3)$$

This expression describes the intuition of a single-period separating equilibrium with charity as a signal of quality. There cannot be too many opportunistic sellers (high α), which would result in all sellers wanting to make charitable donations to escape the discount of non-charity status. Similarly, if there are too few opportunistic sellers (low α), it may not be worthwhile for charity sellers to separate from the (largely ethical) non-charity seller population. We note finally that sellers who have revealed their type with negative feedback can still transact with consumers at price p_2^O, which includes a discount relative to trading with high-feedback non-charity sellers:

$$p_2^{nd} - p_2^O = \gamma(1 - \alpha_2)v \quad (4)$$

Going back to the first period, we once again need a wedge between donation and non-donation prices to ensure separation of G-sellers from E- and O-sellers. The first-period separating condition is identical to that of the second period, except that no seller has yet suffered negative feedback, so the condition becomes $(1 - \theta)d < \gamma\alpha v < d$. The first-period charity premium follows equation (2)'s form, but is larger because $\alpha > \alpha_2$. However, given the opportunity to profit from reputation in period two, separation further requires that O-sellers cannot benefit from spending c for their first item in order to obtain higher prices in the second period. For O-sellers who spend c on their first item, the expected second-period benefit is the price premium from avoiding negative feedback from the first period given in (4), multiplied by the probability of failure. Hence we have the additional requirement:

$$c > \gamma^2(1 - \alpha_2)v. \quad (5)$$

Before proceeding to the empirical analysis, we highlight a few aspects of the model. First, when the model's parameters satisfy equation (3), charity is an effective quality signal. This yields a charity price premium even in the absence of charity-minded consumers. These conditions are easily satisfied as long as charity sellers' utility gain from donating is sufficient, and the proportion of opportunistic (or short-sighted) sellers is neither too high nor too low. More strikingly, as long as the costs of quality-assurance as expressed in (5) are not too low, the charity premium declines with feedback, as performance reveals low-quality sellers. These are the basic insights that we take to the data below.

3. eBay and Giving Works

We analyze data from eBay.com, the world's largest online marketplace. eBay users traded nearly $60 billion in products during 2009, when the site had more than 90 million active users. Merchandise traded ranges from less costly items such as accessories for toys or clothing, to higher-end products including appliances and automobiles. Sellers on eBay offer their goods through "listings" which may be: true auctions, in which bids are collected until a specified ending time (usually seven days after the auction begins); fixed-price listings in which the seller specifies a price and an ending date, often a month or more later; or a hybrid form in which a true auction also includes a "buy-it-now" price which a consumer can pay to end the auction immediately. When a seller creates an eBay listing, he or she provides: a title and subtitle, which generally contain a brief description of the product for sale; a more detailed description and possibly photographs and standardized product specifications; and an auction starting price, buy-it-now price, or fixed price, depending on the listing format. For consumers shopping on eBay, searching a product category initially returns a set of items for which the title, subtitle, starting price, and a single photo are displayed. To see additional details for any individual listing, the consumer clicks to open a separate web page containing the remaining information and photos provided by the seller. For additional details on eBay and the practices within it, see the survey article by Bajari and Hortascu (2004).

To monitor seller quality, eBay maintains a feedback system. A new user begins with a feedback score of zero, and any seller or buyer with whom she has completed a transaction may add a single point to indicate a positive experience or subtract a single point for a negative experience. Virtually all eBay transactions result in a positive consumer evaluation or no evaluation at all, so feedback scores function primarily as descriptors of user experience, i.e., number of completed transactions. Consumers may obtain additional information about seller quality by browsing comments left by other users, or reviewing the seller's performance on a handful of detailed seller ratings (e.g. item as described, shipping time) for which eBay began tallying results in 2007.

In 2003 eBay introduced the Giving Works program, which allows sellers to pledge a portion of their listing revenue to a charity of their choosing. The program is administered jointly with MissionFish, a non-profit company owned by the Points of Light Institute, a registered charity. GW organizes information on and payments to more than 12,000 registered charity groups. For eBay sellers, participating in the GW program is a listing-level choice made along with the standard listing characteristics such as starting price. In addition to selecting the beneficiary charity, the seller chooses a donation percentage from 10% to 100% in increments of 5%. MissionFish receives a small portion of the donation as an administrative fee. On a GW item's individual web page, along with the usual information provided on any product listing, consumers observe the name and logo of the seller's chosen charity, a short description of the charity's mission, and the percentage of revenue pledged. When a consumer purchases a GW item, Missionfish automatically collects the donation from the seller (using payment information on file at eBay), so there is no uncertainty as to whether a seller will follow through on a donation pledge. During the period of our study, eBay did not tally sellers' cumulative donations, nor did it report any measures of charitable giving along with its detailed seller ratings.

Sellers who use GW receive two immediate and concrete benefits from the program. First, they can claim the entire donated sum as a tax-deductible charitable donation (consumers who purchase GW items receive no tax benefit). Second, for each item listed through GW, sellers receive a proportional refund on eBay fees equal to the percentage donated to charity.

3.1 Bidder search

Consumers may encounter GW listings in three ways. First, they are presented along with standard (non-GW) items whenever the GW products' characteristics fit the terms of a consumer's search. Within lists of search results, GW items are distinguished by a small blue and yellow ribbon that appears next to the listing title. GW status does not affect the default listing order. Second, the consumer may use MissionFish or the GW program's central web page to search for items among all GW listings, or to look for those associated with a particular non-profit. Third, consumers may encounter special GW promotions from eBay's front page. These promotions are usually focused on a particular charitable cause or nonprofit organization rather than a product.

Although eBay provides a wealth of information about products and sellers, prior work suggests that consumer search is costly and that bidders do not aggregate all relevant information available on the website before making purchase decisions. In particular, Lee and Malmendier (2011) show that some eBay bidders win auctions at prices higher than contemporaneous buy-it-now (fixed) prices for the same item and that, additionally, the likelihood of this behavior is increasing in how far apart the auction and buy-it-now listings are in the eBay search results. They conclude that bidders fail to pay attention to their full set of opportunities. Similarly, Ariely and Simonson (2003) and Sailer (2006) find results consistent with consumer under-searching and possessing high imputed search costs, respectively.

These studies suggest that in forming expectations about seller quality based on charity commitments, bidders are unlikely to have a complete view of a seller's behavior. Uncovering a seller's donation history is at best time-consuming and at worst impossible. Consumers' charity-related quality inferences, then, are likely to be derived primarily from the presence or absence of a GW donation in the listing of interest, rather than from an examination of the complete history of the seller's giving behavior.

4. Data

4.1 Constructing the estimation sample

eBay provided us with a custom extract of 23.5 million product listings which appeared at eBay.com between January 2004 and March 2008. For each quarter during this period, we obtained data on every listing by a seller who listed any item through eBay's Giving Works program during that quarter. From within the extract, we identified "quasi-experiments" in which a seller posted multiple items with the same title, subtitle, and starting price, but possibly with variation in other listing attributes. In particular, we focus on groups matched along these dimensions that exhibit variation in the share of revenue donated to charity (including otherwise identical listings with a donation equal to zero). We assume that products within a match are identical. Although this approach runs the risk of some over-matching of listings that are actually different, we show in Appendix Table A1 that a listing's GW status within a match is uncorrelated with other observable auction characteristics (e.g. number of photos) that sellers may adjust when items are truly different, and this holds both on average and across sellers with different feedback scores.[5]

To eliminate potentially confounding sources of variation across and within experiments, we narrow the sample in a several ways. First, we eliminate listings from sellers based outside of the U.S. Second, we drop observations in which a seller offers multiple units of an item under a single listing. Third, we eliminate the 2.4 million listings which started in 2004, as many of these have missing data on listing characteristics, and the remaining listings with complete data would add little to the subsample we analyze. Fourth, we keep only listings that are run as true auctions, although some of these include a buy-it-now option. Fifth, we eliminate observations in which the seller independently removes the listing before its ending date (due, for example, to a listing error or a lost or broken item). Listings that end with a buy-it-now sale before the scheduled ending date are not affected by this step, nor are listings that fail to sell because they did not attract any bids above the reserve price. Sixth, to reduce the impact of outliers, we eliminate observations in which the auction's starting price, reserve price, or maximum bid is above the 99.9th percentile within its respective distribution. Finally, we eliminate from the remaining data any groups of matched listings that lack variation in the

[5] In Table A1 we report one significant correlation between a listing's charity status and its other characteristics; the interaction term between a listing's length and log(*feedback*) is positive and significant at the 5% level. Given that we report a total of 14 coefficients, this could well be a spurious correlation that exists by chance.

fraction of revenue donated via GW. We describe the remaining data as our set of seller-product-start price experiments (SPSE). Within this sample we observe 5,015 sellers generating 162,505 listings which contain 22,610 unique seller-title-subtitle-start price combinations. We use the terms "experiment" and "match" interchangeably to refer to sets of auctions with the same seller, title, subtitle, and start price. We note that the results reported below are relatively insensitive to the precise criteria that we use for matching.

For each listing in the SPSE sample, we observe several auction characteristics determined by the seller. These include: the scheduled start and end dates; the secret reserve price, if one exists; shipping fees; an indicator for a buy-it-now option; indicators for whether the item was listed in bold and (separately) whether it was "featured" within listings of search results; the number of photos included on the listing page, top-coded at 8; and the item's top-level eBay product category designation (e.g. "Consumer Electronics"). In addition, for each auction we observe the following variables that are determined by bidders' responses to the listing: the number of bids; the maximum bid value submitted; an indicator for whether the item was sold; and the sale price of the item, provided it sold. A third of listings in our SPSE sample ended in a sale, but a greater fraction attracted bids—in 6% of listings, consumers submitted bids but no sale occurred because the greatest bid was below the (hidden) reserve. Finally, for each listing we observe the seller's feedback rating when the auction began; we also observe the date that the seller created his eBay account, which we use to calculate the seller's "age" at the auction's start date.

4.2 *Summary statistics*

In Table 1 we present summary statistics from the SPSE sample. Panel A of Table 1 contains information on the 5,015 unique sellers in the data. There is an average of 4.5 distinct title-subtitle-start price combinations and 32.4 listings per seller, but the median numbers of matches and listings per seller are considerably smaller due to a handful of sellers who account for hundreds of matches or listings apiece. We report in Table 1 an individual seller's average age in days and feedback rating by taking the mean across all of the seller's listings within the sample. Consistent with the skewing of the data by some large sellers, the mean feedback value is 889, while the median is 148. In the analysis of Section 5, we account for changes over time in sellers' feedback by computing the mean feedback level for the set of auctions in each experiment. Among the 2,021 sellers with multiple experiments in the SPSE data, the average seller is active in 1.9 eBay top-level product categories.

In Panel B of Table 1 we display match-level characteristics of the SPSE data. We focus on variation in auction characteristics within each match. The average match has half of its listings associated with GW. Within matches, there is some limited variation in seller-chosen listing features. Nearly 28% of matches include some variation in scheduled duration. Similarly, about 27% of matches include variation in one or more of the following: reserve price, shipping fees, bold status, featured status, and number of photos. We control for these features in the analysis below.

Panel C of Table 1 contains auction-level summary statistics from the SPSE sample. The median listing neither sells nor attracts a bid, but among the 33% of auctions that are successful the mean price is $78.31 (median $22.22). Among GW auctions in the SPSE sample, about two-thirds have all revenue donated to charity, and a quarter of auctions donate 10% of revenue. The third-most common donation value, 50%, appears in only 2.5% of Giving Works auctions in the SPSE sample. In the sample, there is relatively little within-seller variation in positive donation rates – 20% of the GW listings in our final dataset come from sellers with only 10% donation levels, and an additional 61% come from sellers with exclusively 100% donations. While sellers in our sample who pledge 100% donations may do so primarily to satisfy their private charitable goals, for our purposes these auctions are nonetheless useful for understanding consumers' responses to seller charity. In a setting where seller donations may be used to signal other-regarding concerns, giving 100% to charity is the strongest possible signal of preferences for fair-dealing.

Sellers in the SPSE sample pledge donations to 2848 different nonprofit organizations; the top 10 charities account for 41% of all GW listings in the sample. Sellers with multiple GW listings in the SPSE data tend to concentrate their donations individually toward a small number of organizations. Among these 2736 sellers, the median number of nonprofits per seller is 1, while the mean is 1.5.

4.3 Giving Works activity in context

The quasi-experiments we analyze represent a small fraction of GW activity. Between January 2004 and March 2008 we observe 2.1 million GW listings offered by 78,037 unique sellers. About 5,600 sellers acted as non-profits, and always donated all of their revenue;

however, these sellers account for only 150,000 listings. Thus the bulk of GW activity – more than 1.8 million listings in all – comes from sellers who attempt at least sometimes to profit from sales and also do not engage in experiments, as we define them above. Those for-profit sellers who do use GW during 2004-08 list approximately 9% of their products via GW. In 73% of GW listings by these sellers, 100% of revenue is pledged to charity, and an additional 18% of listings pledge 10% of revenue.[6]

Figure 1 displays quarterly statistics on GW activity by donation level for US-based items between 2004 and the first quarter of 2008, with the number of GW listings measured on the left axis and the number of unique GW sellers on the right axis. Use of the program increased steadily over the period of our study, with the exception of a decline during 2007 Q2. (eBay reports that the use of GW has grown substantially since the end of our sample period.) The number of GW listings exhibits some modest seasonality, with peak usage typically occurring in the final three months of the year. Of note is the three-fold increase in the number of 10% and mid-level donations between 2005 Q2 and 2005 Q3, when Hurricane Katrina struck New Orleans, and the subsequent fall in these GW listings during 2005 Q4. The figure also shows that the usage of the GW program, as measured by the number of unique sellers making a GW listing, peaked during the third quarter of 2005 in the aftermath of

[6] When we examine the frequency of GW use by for-profit sellers during 2004-08 and control for seller-level average GW frequency, we find that sellers typically reduce their GW use as their eBay feedback ratings increase. This is consistent with charity listings being a substitute for accumulated feedback in assuring consumers that a seller or product is of high quality, but may also be consistent with alternative explanations, such as learning that the charity premium is less than anticipated. Unfortunately our data do not lend themselves to evaluating sellers' dynamic donation choices, as we do not observe sellers' actions during quarters when they do not post GW auctions and therefore cannot assess sellers' success or longevity after their final quarter of GW activity.

Hurricane Katrina, but otherwise exhibits an upward trend that mirrors the growth of GW listings.

GW listings are a small share of overall activity on eBay, but GW users are largely similar to the marketplace's other sellers. eBay provided us with summary statistics on auction listings offered by *all* US-based sellers who used the site during the second quarter of 2009. In appendix Table A2 we display these statistics grouped by sellers' feedback levels and GW participation. While some differences are apparent in the table (e.g. shipping fees from ever-charity sellers are about 10-15% lower than other sellers' fees), these differences are small relative to the variance in the listings' characteristics within each group.

5. Analysis

Our analysis proceeds in three parts. We begin by estimating how consumers' responses to sellers' charity varies with the sellers' levels of eBay experience. Next we show that these results are robust to a range of alternative explanations. We then explore some additional predictions implied by charity serving as a credible signal of seller quality, by (a) providing evidence that sellers who more often post charity listings have fewer customer complaints, and (b) assessing whether charity tie-ins are profitable for sellers.

To estimate the consumer response to charity tie-ins, we employ the following basic specification:

$$\begin{aligned} Y_{ism} = \; & \alpha_{sm} + \beta' DONATION_{ism} + \gamma' DONATION_{ism} \times FEEDBACK_{sm} \\ & + \theta' CONTROLS_{ism} + \varepsilon_{ism} \end{aligned} \tag{6}$$

where s indexes the seller, m represents a title-subtitle-start-price matched group of listings, and i is a sub-index within each match for a specific listing; α is a fixed effect by match and seller. We examine four different dependent variables (Y). In our main analysis we estimate the probability of sale and the natural log of the maximum bid submitted by any bidder. In supplementary analyses we also report results on the number of bids submitted and the log of the ending price of the auction conditional on the product selling.[7] The variables in *DONATION*, which vary across specifications, reflect the presence and levels of charitable donations via GW. *FEEDBACK*, which also varies by specification, contains variables that measure a seller's experience level. The key parameters we estimate are in γ, which reflect how consumers' responses to charity vary with seller experience. *CONTROLS* includes indicator variables for the use of bold titles and featured status; indicators for the scheduled length of the listing and day of the week it was expected to close; the number of pictures; an indicator variable for the "buy-it-now" option; controls for differences in shipping and reserve prices across items in the match;[8] and the scheduled end date of the auction, which controls for time trends in demand for identical items on the site. In all analyses, we report standard errors clustered by seller since the main variation of interest is at the seller level. This approach helps account for the widely varying numbers of listings by seller in our dataset.

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[7] If there is only one bidder, this value is equal to the starting price, otherwise it reflects the second-highest bidders' bid. We use maximum bid as our preferred outcome as it is not affected by seller reserve prices, as explained below.

[8] For both shipping fees and (separately) reserve prices, we take the difference between any individual listing's value of the variable and the minimum across all values in match m. In our empirical models we include both this difference and its square as controls.

5.1 Charity impact and seller experience

We begin by estimating equation (6) using only a single dummy variable, *Charity*, in *DONATION* which is equal to one for all GW listings regardless of donation level. We report these results in Table 2. In estimating the impact of charity and seller experience on sale probability, we employ a linear probability model, which facilitates interpretation of the marginal effects of charity. We omit observations where either none or all of the listings within a group result in sales, as we would in a model that explicitly accounts for the binary dependent variable. In Table 2 and subsequent analyses we omit reporting the coefficient estimates for the variables in *CONTROLS.* We report these coefficients in Appendix Table A3 for our baseline specifications for each outcome variable.

In Table 2's column (1) we report that, across all sellers in our sample, having a charity listing is associated with a 10.1 percentage point higher probability of sale (significantly different from zero at $p < .01$). Given the mean sale probability of 33%, this represents a 30% increase in the likelihood of making a sale. In column (2) we interact *Charity* with *Feedback*, which we define to be the natural log of a seller's average feedback across matched listing observations. In column (3) we interact *Charity* with a set of feedback quartile interactions, where the quartile cutoffs are 30, 146.5, and 526.2. We find significant heterogeneity in the effect of charity by seller feedback. In all cases, these interaction's coefficients are negative and significant at the 1% level, indicating a lower GW premium for higher feedback sellers. In column (3), we see that in the lowest quartile of seller feedback, i.e., sellers with feedback scores of less than 30, the increase in sale probability associated with GW auctions is 38.5

percentage points. The remaining interaction coefficients describe a monotonic decrease in the GW sale probability premium as a function of seller feedback. The largest drop in the impact of GW is between the bottom and second-lowest quartile.

In columns (4)-(6) we use the logarithm of the listing's maximum bid as the outcome variable. These results similarly reveal a positive and significant average impact of charity on a listing's maximum bid, an effect that is substantially larger for low-feedback sellers. While the average effect of *Charity* on maximum bid is a premium of 4%, a seller in the lowest feedback quartile receives an average premium of about 17%. As with sale probabilities, the bid premium's size is monotonically decreasing across feedback quartiles.[9] In this analysis we use the highest bid, rather than price, because the bid value always reflects a bidder's choice. When a listing attracts only a single bid, the sale price is the seller's choice of opening price, and reveals less about consumers' inferences about a listing's quality.

In Table 3, we allow the effect of charity to vary by donation percentage. We use one dummy variable for 10% donation listings, a second for 100% donation listings, and a third for all intermediate donation shares. Columns (1) and (4) reveal that the overall effects of charity on sale probability and maximum bid are increasing in the share of revenue donated. In the remaining columns of Table 3 we interact *DONATION* with measures of seller feedback, and again we find that charity's benefits are decreasing in the seller's observable experience for each donation level. These results suggest that all levels of donation may serve as signals of

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[9] The GW coefficients for fourth-quartile sellers in the *Sold* and log(*Max. Bid*) models are significantly different from zero at $p < 0.01$ and $p < 0.10$ respectively.

seller quality in the absence of an established performance track record.

5.2 Robustness of the main results

We have interpreted our results as reflecting a "trust" premium associated with charity for low feedback sellers, i.e., those lacking alternative sources of quality assurance. There may, however, be other differences in the types of product or seller attributes that account for this differential impact of charity on auction outcomes. We now consider a variety of alternative explanations for our reported results.

One particularly important conjecture is that high-feedback sellers might offer different products than low-feedback sellers, and these products may have less scope for quality uncertainty (and therefore signaling) or attract consumers who are less interested in charity. In Table 4 columns (1) and (2) we augment our models with a set of interactions between *Charity* and dummy variables for 33 top-level product categories. This provides a broad set of controls that would account for product-level differences in sellers or customer types. If, for example, video game consumers have a low taste for charity and high-feedback sellers are frequent sellers of video games, then the relevant interaction term will pick up this effect. In these specifications we find that the coefficients on the *Charity* × *Feedback* interactions are marginally higher than those reported in Table 2, suggesting that differences in the types of products for sale across feedback levels are unlikely to account for our findings.

In the remaining columns of Table 4 we display results that examine other alternative theories. For columns (3) and (4) we create dummy variables for the 60 nonprofit organizations that appear most frequently in our data as beneficiaries, and we interact these with the *Charity* variable in the same way we treated the product category dummies in specifications (1) and (2). This allows each popular nonprofit to have its own premium. Nonprofits that are too small to have their own dummy variables are collected together as the omitted category, and their average premium is captured by the coefficient on *Charity*. We find that the main qualitative pattern in our results is unaffected, although the coefficient estimates are slightly smaller than in our base specification. Next, in columns (5) and (6) we investigate whether variation in the number of photos affects the GW premium and its interaction with seller feedback. Although Lewis (2011) finds that more photos for a listing reduce quality uncertainty in the market for automobiles, we find only a weak positive association between the number of photos and sale probability after incorporating seller-item-start price fixed effects; moreover, we find the charity premium to be unaffected by the number of photos in the listing. In columns (7) and (8) we include an interaction between an item's start price and *Charity*, to account for possible correlation between an item's value and consumers' likelihood of paying a charity premium for high-priced items, which may be offered more frequently by high-feedback sellers. Our results remain robust to this additional control.

Finally, in columns (9) and (10) we control for whether there is temporal overlap among GW and non-GW listings in a SPSE-matched group. We identify the relevant listings with the variable *Overlap*. For GW listings, *Overlap* = 1 when there is at least one non-GW listing in its matched group that is open at the same time. For non-GW auctions, *Overlap* similarly denotes whether there is at least one date-overlapping GW auction.[10] When we add the interaction of *Overlap* and *Charity* as a control, we find that the coefficient on this variable is negative in column (9) for sale probability, though not statistically significant. The interaction term's coefficient is very close to zero in column (10) for maximum bids.[11] The coefficient on *Charity* × *Feedback* is virtually unchanged for both sale probability and maximum bid.

As an additional robustness check, we examine whether the main patterns in our data hold within product categories. In Table 5 we provide results on sale probability and maximum bid for the six categories with the most matches by sellers below the median feedback level. The listings we focus on in Table 5 account for about half of all matches by low-feedback sellers. Within each category we find that the baseline effect of charity on sale probability is significantly positive, and the interaction of *Charity* and *Feedback* is consistently negative and significant. Our results on the maximum bid are less often significant – unsurprising given the relatively small sample sizes involved – but the signs of the estimated coefficients are consistent with our main results in Table 2.

Given that we utilize natural variation in seller feedback, we cannot completely rule out the universe of explanations based on unobserved seller differences; however in a collection of supplementary tests, we find that our main results are invariant to a broad range of alternative hypotheses and specifications. We report these tests in an online appendix. We verify that

[10] We experimented with a variety of definitions that were sensitive to the extent of overlap based on fraction of days overlapping and/or fraction of overlapping listings. In practice, this had very little effect on the results.

[11] If we limit the sample to low feedback sellers, the *Overlap*×*Charity* term is significant at the 1% level, indicating a smaller impact of charity on sales probability for overlapping auctions. This could plausibly be the result of reputational spillovers across auctions (of identical listings), with the effect only appearing for sellers without buyer feedback as a quality signal.

estimating the sale probability with a conditional logit model yields the same results as our linear probability specification. We also confirm that our results are unchanged when we exclude all groups of auctions with variation in their characteristics in *CONTROLS* other than ending date. Adding a fixed effect for each date in the sample does not affect our results, nor does interacting *Feedback* with the characteristics in *CONTROLS*, including a measure of the seller's chronological "age" on eBay, controlling for the degree to which a seller specializes in a small number of product categories, or excluding observations from 24 sellers who each have 1,000 or more listings in the SPSE sample. We investigate whether the presence of a seller-provided shop-keeping unit (SKU) code reduces the scope for quality uncertainty and signaling, but our main results are unaffected by this additional control for heterogeneity across products in the SPSE sample. Likewise, the presence of quality-assurance language in a listing title (e.g. "guaranteed," "certified," or similar) has no effect on the magnitude of the *Charity* coefficient or its interaction with *Feedback*. We refer the reader to the online appendix for additional details on these tests.

5.3 Charitability and seller-initiated disputes

We next examine the relationship between a seller's propensity to donate and a measure of transaction performance: whether the transaction results in a dispute. This tests a central assumption in our signaling model – that donations are less likely to be made by sellers who provide consumers with poor service. Although all sellers in our sample have listed at least one charity auction, there is substantial variation in sellers' propensity to use GW, ranging from less than 1% to 100%. We assume that sellers with minimal but positive GW activity are not too different from sellers who completely forego charity on eBay. Within this sample we examine whether sellers' donation propensity is significantly correlated with the probability that a completed sale leads to an "unresolved dispute" between the seller and buyer.[12] We focus on likely buyer-initiated disputes by counting only those unresolved disputes associated with transactions in which the buyer completed payment within 30 days of the auction end date.[13] The principle buyer-initiated disputes that arise on eBay are "item not received" and "item not as described."

We observe an indicator for unresolved disputes beginning in the third quarter of 2006. Our master data set contains 14.5m listings that began between July 2006 and March 2008, and of these approximately 35% ended in a sale. We focus on successful single-item listings by U.S.-based sellers who are not registered as non-profits with eBay.[14] This provides over 2.7m listings with information on the presence of a dispute plus complete data on seller and listing attributes. We identify buyer-initiated disputes in roughly 1% of these transactions.

To construct measures of sellers' "charity intensity," we use data from the full sample period. We calculate two measures of a seller's charity intensity: the share of all listings that

[12] During the period of our study, eBay contracted with third-party mediation services, such as SquareTrade, to support the resolution of these disputes. This dispute resolution process is described in detail in Freidman et al. (2004), who report that fewer than half of all disputes in their sample were ultimately resolved.

[13] We inferred that disputes were initiated by the seller if the buyer had not paid, or had paid the seller only after the accepted period of time.

[14] Non-profit sellers may have different objectives than profit-seeking sellers, and also are easy for consumers to identify because their seller names match the GW donation recipients.

are GW, and the share of all eBay revenue that the seller donates to charity.[15] Table 6 provides summary statistics on sellers' charity intensity (upper panel) and its correlation with dispute rates (lower panel). We report statistics for all sellers together and with sellers separated into coarse bins by their average feedback score during their histories in our data. Sellers with more eBay activity generally have lower measures of charity intensity, although the reported percentiles of charity listing frequency show variation within feedback strata. Across the entire sample, a seller's likelihood of receiving a dispute is negatively correlated with her charity intensity. This correlation holds within feedback bins as well.

We estimate a set of linear probability models to establish robustly that a seller's overall charity intensity is negatively correlated with his or her probability of having an unresolved dispute. In focusing on individual sales, we are able to include a range of control variables that may contribute to differences in dispute rates across products and sellers. We include controls for seller feedback, the item's starting price, selling price, other listing characteristics, and a dummy variable for each top-level eBay product category. We report our results in Table 7. In column (1) we find that sellers with a greater share of charity listings have a significantly lower chance of an unresolved dispute on an individual transaction. With an overall rate of 1.1% for unresolved buyer-initiated disputes in this sample, the estimate implies that sellers who use GW for all of their products have a dispute rate that is about 40% less than that of sellers who use GW very rarely. In (2) we report that the same negative relationship

[15] These shares generally over-estimate a seller's charity intensity, as they omit quarters during which the seller posted no GW listings, and therefore are not in our data.

exists between the unresolved dispute rate and the seller's share of donated revenue. These results are robust across seller sizes. In columns (3) and (4) we limit the sample to sellers with average feedback scores below 100, and we find very similar results to those from the full sample. In (5) we verify that the main effects of charity intensity are not driven by buyers' reluctance to register disputes on charity items. Our main results are not substantially affected by the inclusion of dummy variables for the donation amount attached to an individual listing (conditional on the sellers' average charity level), nor are any of the charity dummies themselves significant. Finally, in (6) we take a less parametric approach, dividing sellers into quartiles by charity intensity. We find that as sellers increase through quartiles of charity frequency, their unresolved dispute rates decline significantly and monotonically. Overall, we find consistent evidence that sellers with a greater share of charity activity are less likely to disappoint their customers.[16]

5.4 Profitability of charity tie-ins.

The separation condition that determines whether charity signals seller quality requires that opportunistic sellers are not tempted to use charity to boost profits.[17] While our simple theoretical model only incorporates the benefit of a higher sales price, this intuition may be extended to include both sale probability as well as price conditional on selling, with the basic

[16] In separate analysis, we use the data from Elfenbein and McManus (2010b) on listings by charity and non-charity sellers during September-October 2006. Those data contain information on a seller's percentage of positive feedback, and not just the raw score. In analysis that we describe in the online appendix, we find that non-charity sellers are more likely to have very low positive feedback percentages.

[17] In this section, we assume that sellers are businesses which would deduct the charitable contribution as a business expense. For this set of sellers, there are no incremental tax benefits of GW sales.

separating condition requiring that the combined financial benefit from higher sale probabilities and prices not exceed the cost of donating. We investigate this condition by comparing selling strategies in which a seller commits to offering an item via GW until it sells, or outside of GW until it sells. Recall that the expected non-charity price of an item is p^{nd}, conditional on selling. Define the probability of a non-charity sale as q^{nd} and β as the per-listing-period discount rate. The present discounted value of revenue from committing to non-charity listings is thus $U^{nd} = p^{nd}q^{nd} + (1-q^{nd})\beta U^{nd}$. The discounted revenue value from a GW listing (superscripted with d), which may have a different sale probability and price, is $U^{d} = q^{d}(1-\eta)p^{d} + (1-q^{d})\beta U^{d}$, where η is the fraction of revenue donated to charity. In Appendix 2 we extend these expressions to account for eBay fees, which are partially discounted in GW listings, and the daily decline in sale probabilities and expected prices reported in Table A3. Even if using GW provides no price premium and sellers are perfectly patient, an increase in sale probability has the benefit of reducing (expected) future fees from re-listing unsold items. (We abstract from considering the seller's profit-maximizing choice of a reserve price, which in general could be different across charity and non-charity auctions.)

In Table A5 we explore the expected value of pursuing a GW selling strategy using our estimates for 10% donations, and compare it to the expected value of the non-GW selling strategy.[18] The analysis shows that 10% donations do not provide a greater present value, net of fees and donations, than committing to non-GW listings. A 10% donation strategy yields, on average, 93.9% of the net discounted revenue of selling via a non-GW strategy. Even for

[18] In our calculations we employ the predicted price premium for 10% GW listings, which we report in Table A4.

low-feedback sellers, pursuing a 10% donation strategy yields only 95.9% of the discounted revenue of a non-GW strategy.[19] These calculations also indicate that, for sellers committed to making donations either within or outside of their eBay activity, Giving Works is an efficient way for sellers to pursue their altruistic goals.

In summary, we find that our estimates are broadly consistent with the intuition provided by equation (3), at least as it relates to returns from a single sale. We recognize that our analysis does not incorporate the potential benefit to low-feedback sellers from donations that enable the rapid accumulation of positive feedback. For low-feedback sellers with high discount rates and large inventories of potential listings, we cannot definitively rule out the possibility that dynamic benefits enable donating to have positive returns on a purely pecuniary basis.

6. Conclusions

Using a sample of more than 22,000 quasi-experiments performed by eBay sellers, we explore the quality inferences that consumers make when a fraction of the proceeds from their purchases are donated to charity. We find that linking product sales to charitable donations yields substantial benefits for eBay sellers with short track records of satisfactory performance, and small but positive benefits for sellers with extensive feedback. These patterns are robust to a wide range of alternative specifications. Our results are consistent with a model of charity as a signal of seller quality or trustworthiness, and we show that additional predictions of this

[19] See the notes below Table A5 for the numerical assumptions for these calculations.

model – on the profitability of charity sales and the customer satisfaction rates of charity sellers – also hold in the data. While prior theoretical work has largely relied on assumptions about consumers' preferences for public goods (e.g., Bagnoli and Watts 2003, Baron 2007, Besley and Ghatak 2007), our analysis suggests that even consumers who receive no utility from making donations may be willing to pay more to purchase from charity-oriented sellers. To be clear, we do not seek to refute the notion that many consumers derive incremental utility from purchasing products with charity ties, but rather we seek to describe an additional mechanism through which charity ties can affect consumer demand.

Our paper has a number of limitations. A maintained assumption behind our investigation of signaling is that consumers have only imperfect information about the current and historical charity activity of eBay sellers. We believe that this assumption is reasonable in this context, because eBay does not record or reveal a seller's charitable donations for easy use by potential customers. However, to the extent that potential bidders actually do investigate sellers and draw quality inferences from past charitable donations, our estimates of benefits from charity links will be under-estimated. A second limitation is that our assessment of the full benefits of charitable endeavors is incomplete. In future work, we seek to address the degree to which charity tie-ins are useful in building valuable reputations, in repairing reputations after bad outcomes, and in generating spillover benefits to other products. Finally, it bears noting that our empirical setting (and hence the assumptions in our simple model) involves considerable opportunities for seller moral hazard. Where goods or services are easy to inspect, sellers have well-established reputations and product lines, or where quality-contingent contracts are easy to enforce, we expect consumer utility concerns rather than quality signaling to be the dominant driver of any observed "charity premium."

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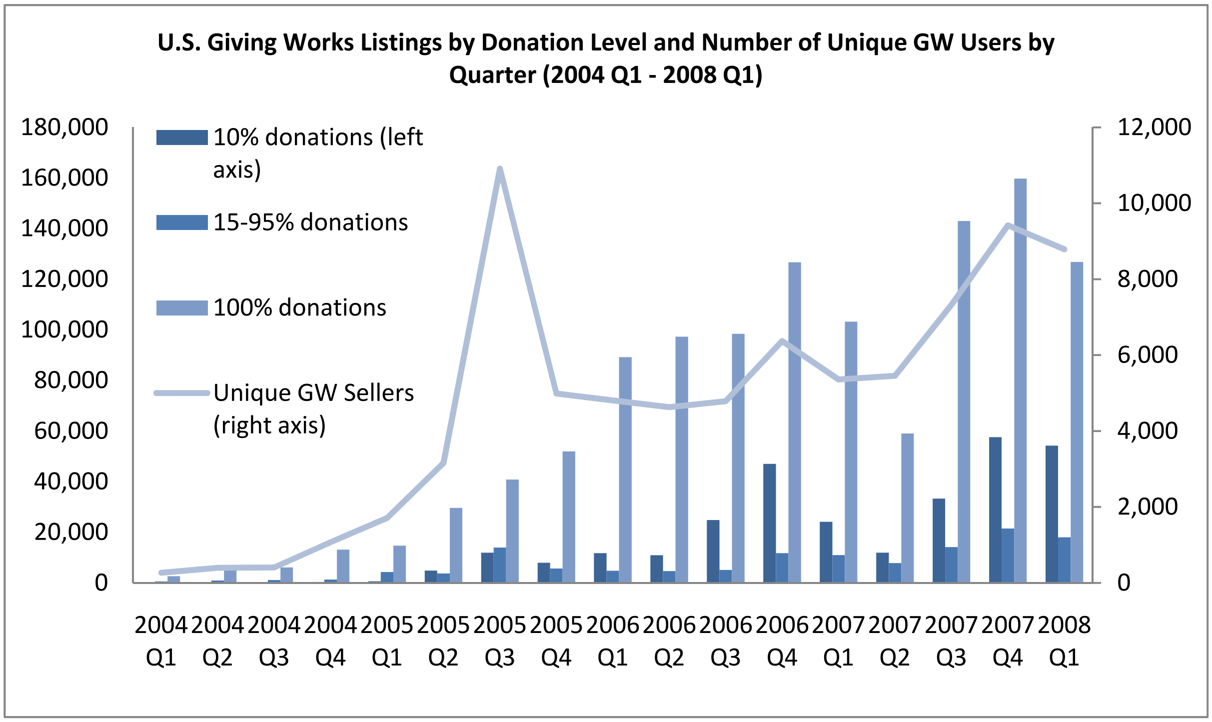
Figure 1. Growth of Giving Works listings over time



Notes: The axis on left is for the number of charity listings per quarter. The axis on the right is for the number of sellers using Giving Works in the quarter.

Table 1: Summary statistics on sellers, matches, and listings

	Mean	Median	Std. Dev	Min	Max
Panel A: Sellers (N = 5015)					
N Matches	4.51	1	30.96	1	1356
N Listings	32.40	4	298.49	2	14642
Avg. feedback	889.34	148.25	4485.45	0	136297.4
Avg. age (days) *	1373.24	1284.49	984.39	0	4064.3
N top-level categories *	1.90	1	1.81	1	25
Panel B: Matches (N = 22,610)					
N Listings	7.19	3	19.17	2	1092
Donation > 0 (1= yes)	0.50	0.5	0.20	0.002	0.996
Difference in start date	34.84	14.31	58.69	0	866
Indicator on whether match has variation in…					
Reserve price	0.028	0	0.166	0	1
Shipping fee	0.125	0	0.330	0	1
Scheduled length	0.278	0	0.448	0	1
Bold	0.026	0	0.158	0	1
Featured	0.014	0	0.118	0	1
Buy-it-now option	0.087	0	0.281	0	1
Photo Count	0.049	0	0.216	0	1
Panel C: Listings (N = 162,505)					
Success	0.33	0	0.47	0	1
Number of bids	2.63	0	6.07	0	159
Sale price *	78.31	22.22	244.58	0.01	4450
Maximum bid *	223.96	31.11	520.37	0.01	6602
Start price	42.10	9.99	189.70	0.01	9999
Reserve price	147.88	12.59	541.46	0.01	9999
Shipping fee	6.26	4.99	12.34	0	3595
Scheduled length	6.23	7	2.05	1	30
Actual length	6.02	7	2.21	0	30
Bold	0.03	0	0.18	0	1
Featured	0.02	0	0.13	0	1
Buy-it-now option	0.33	0	0.47	0	1
Photo Count	1.24	1	1.19	0	8
Non-Giving Works only (N = 75,618)					
Days between own start	47.75	21	78.52	0	964
Giving Works only (N = 86,887)					
Donate 10%	0.27	0	0.44	0	1
Donate 15-95%	0.10	0	0.30	0	1
Donate 100%	0.63	1	0.48	0	1

Notes: Seller age is not available for all sellers; N = 4,723. We compute the number of top-level product categories for sellers with multiple matches; N = 2,021. N for sale price is 54,416. N for maximum bid is 63,689.

Table 2: Seller feedback and the effect of charity status on sale probability and maximum bid

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Sold	Sold	Sold	Log(Max. bid)	Log(Max. bid)	Log(Max. bid)
Charity	0.102***	0.332***	0.386***	0.0402***	0.132***	0.171***
	(0.0159)	(0.0574)	(0.0728)	(0.0104)	(0.0328)	(0.0458)
Charity		-0.0324***			-0.0132***	
× log(Feedback)		(0.00758)			(0.00392)	
Charity			-0.217***			-0.115**
× 2nd feedback quartile			(0.0764)			(0.0510)
Charity			-0.286***			-0.136***
× 3rd feedback quartile			(0.0746)			(0.0490)
Charity			-0.332***			-0.155***
× 4th feedback quartile			(0.0733)			(0.0467)
Observations	103592	103,159	103,592	63689	63,294	63,689
R-squared (within)	0.013	0.018	0.020	0.008	0.009	0.010

Notes: In addition to the variables above, we include variables in *CONTROL* that are displayed in Table A3 and described in that table's notes. Standard errors, clustered on seller, are in parentheses. *** indicates significance at $p = 0.01$, ** for $p = 0.05$, and * for $p = 0.10$.

Table 3: Seller feedback and the effect of charity by donation share on sale probability and maximum bid

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Sold	Sold	Sold	Log(Max. bid)	Log(Max. bid)	Log(Max. bid)
Donation=10%	0.0586***	0.166***	0.123***	0.0217**	0.0631***	0.0423
	(0.0118)	(0.0288)	(0.0320)	(0.00917)	(0.0238)	(0.0383)
Donation=10%		-0.0136***			-0.00547**	
× log(Feedback)		(0.00368)			(0.00279)	
Donation=10%			0.0250			0.00487
× 2nd feedback quartile			(0.0464)			(0.0453)
Donation=10%			-0.0515			-0.0114
× 3rd feedback quartile			(0.0405)			(0.0444)
Donation=10%			-0.0893***			-0.0309
× 4th feedback quartile			(0.0340)			(0.0397)
10%<Donation<100%	0.102***	0.308***	0.302***	0.0474**	0.111*	0.257***
	(0.0196)	(0.0638)	(0.0907)	(0.0186)	(0.0568)	(0.0701)
10%<Donation<100%		-0.0297***			-0.0102	
× log(Feedback)		(0.00820)			(0.00756)	
10%<Donation<100%			-0.122			-0.278***
× 2nd feedback quartile			(0.102)			(0.101)
10%<Donation<100%			-0.220**			-0.223***
× 3rd feedback quartile			(0.0950)			(0.0757)
10%<Donation<100%			-0.224**			-0.213***
× 4th feedback quartile			(0.0937)			(0.0749)
Donation=100%	0.137***	0.553***	0.539***	0.0617**	0.266***	0.246***
	(0.0333)	(0.103)	(0.0885)	(0.0240)	(0.0718)	(0.0583)
Donation=100%		-0.0640***			-0.0322***	
× log(Feedback)		(0.0138)			(0.00953)	
Donation=100%			-0.353***			-0.134**
× 2nd feedback quartile			(0.0970)			(0.0677)
Donation=100%			-0.403***			-0.204***
× 3rd feedback quartile			(0.0927)			(0.0678)
Donation=100%			-0.475***			-0.233***
× 4th feedback quartile			(0.0915)			(0.0611)
Observations	104083	103650	104083	63841	63446	63841
R-squared (within)	0.015	0.021	0.024	0.008	0.010	0.011

Notes: Standard errors, clustered on seller, are in parentheses. *** indicates significance at $p = 0.01$, ** for $p = 0.05$, and * for $p = 0.10$. See Table 2 for additional notes.

Table 4: Robustness of results to alternative sources of variation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Additional controls:	Category dummies		Nonprofit dummies		Number of photos		Start Price		Overlapping listings	
Dependent Var.	Sold	log(Max. bid)	Sold	log(Max. bid)	Sold	log(Max. bid)	Sold	log(Max. bid)	Sold	log(Max. bid)
Charity	0.366***	0.133***	0.289***	0.0930***	0.329***	0.132***	0.315***	0.151***	0.323***	0.131***
	(0.0525)	(0.0491)	(0.0303)	(0.0252)	(0.0582)	(0.0328)	(0.0584)	(0.0359)	(0.0586)	(0.0331)
Charity × log(Feedback)	-0.0362***	-0.0147***	-0.0261***	-0.00912**	-0.0321***	-0.0132***	-0.0330***	-0.0135***	-0.0309***	-0.0130***
	(0.00704)	(0.00436)	(0.00419)	(0.00354)	(0.00765)	(0.00391)	(0.00736)	(0.00402)	(0.00761)	(0.00413)
Photos					0.0204	-0.0200				
					(0.04577)	(0.06084)				
Photos × Charity					0.00003	0.0062				
					(0.00609)	(0.00888)				
log(Start Price) × Charity							0.00754	-0.00775*		
							(0.00700)	(0.00456)		
Overlap									-0.0094	0.00328
									(0.0121)	(0.0171)
Overlap × Charity									-0.0184	0.00275
									(0.0219)	(0.0168)
Dummies for product categories × Charity?	Yes	Yes	No	No	No	No	No	No	No	No
Dummies for nonprofit organizations × Charity?	No	No	Yes	Yes	No	No	No	No	No	No
Observations	103592	63294	103,159	63,294	103159	63,294	103650	63446	103424	63294
R-squared (within)	0.023	0.011	0.027	0.012	0.018	0.009	0.019	0.009	.018	.009

Notes: Standard errors, clustered on seller, are in parentheses. *** indicates significance at $p = 0.01$, ** for $p = 0.05$, and * for $p = 0.10$. See Table 2 for additional notes.

Table 5: Seller feedback and charity's impact within individual product categories

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Sold	log(Max. bid)	Sold	log(Max. bid)	Sold	log(Max. bid)
Product category:	Collectibles		Books		Jewelry & Watches	
Charity	0.403***	0.307**	0.506***	0.0293	0.397***	0.358**
	(0.0981)	(0.128)	(0.114)	(0.0988)	(0.151)	(0.149)
Charity × log(Feedback)	-0.0439***	-0.0430**	-0.0618***	-0.000713	-0.0337*	-0.0465**
	(0.0139)	(0.0188)	(0.0155)	(0.0126)	(0.0194)	(0.0208)
Observations	9,632	4,608	7,567	2,915	6,121	3,084
R-squared	0.025	0.031	0.021	0.015	0.039	0.025
Product category:	Clothing, Shoes & Accessories		Home & Garden		Tickets & Travel	
Charity	0.302***	0.128***	0.283***	0.110	0.665***	0.334***
	(0.0566)	(0.0418)	(0.0940)	(0.0839)	(0.112)	(0.109)
Charity × log(Feedback)	-0.0246***	-0.0110**	-0.0309**	-0.0131	-0.0788***	-0.0374***
	(0.00656)	(0.00430)	(0.0125)	(0.0126)	(0.0136)	(0.0127)
Observations	18,270	11,218	13,122	6,316	3,309	3,689
R-squared (within)	0.062	0.013	0.010	0.011	0.273	0.101

Notes: Standard errors, clustered on seller, are in parentheses. *** indicates significance at $p = 0.01$, ** for $p = 0.05$, and * for $p = 0.10$. See Table 2 for additional notes.

Table 6: Descriptive Statistics on Charity Intensity and Unresolved Disputes

	All sellers	Seller feedback 0-100	Seller feedback 100-1000	Seller feedback 1000+
Seller charity share of:				
All listings	0.3377	0.4405	0.2628	0.0872
Total revenue	0.1575	0.2030	0.1214	0.0589
Charity listing frequency at:				
25^{th} percentile	0.0362	0.1000	0.0250	0.0039
50^{th} percentile	0.1667	0.3333	0.0986	0.0124
75^{th} percentile	0.5714	0.8261	0.4000	0.0447
N sellers	22,349	11,448	8,842	2,059
Unresolved dispute = 1	0.0112	0.0065	0.0077	0.0128
Correlation between dispute = 1 and seller charity share of:				
All listings	-0.0174	-0.0158	-0.0146	-0.0119
Total revenue	-0.0151	-0.0161	-0.0133	-0.0103
N successful listings	2,716,661	202,521	623,885	1,890,255

Table 7: Seller Charity Intensity and Unresolved Dispute Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Does the sale have an unresolved dispute? (Yes = 1)					
Seller charity share of:						
All listings	-0.00410***		-0.00333***		-0.00490**	
	(0.00147)		(0.000652)		(0.00194)	
Total revenue		-0.00361**		-0.00342***		
		(0.00148)		(0.000611)		
Seller charity listing freq.						
2^{nd} quartile						-0.000744
						(0.000805)
3^{rd} quartile						-0.00426***
						(0.00102)
4^{th} quartile						-0.00429**
						(0.00172)
Indiv. item GW status						
Donation = 10%					-0.00104	-0.000383
					(0.000996)	(0.000942)
10% < Donation < 100%					-0.000199	0.000264
					(0.000867)	(0.000845)
Donation = 100%					0.000922	0.000549
					(0.00112)	(0.00118)
Seller population	All	All	Feedback < 100		All	All
Observations	2,716,661	2,716,661	202,521	202,521	2,716,661	2,716,661
R-squared	0.003	0.003	0.002	0.002	0.003	0.003

Notes: All models include additional control variables. These variables include dummies for: each month in the data (July 2006 – March 2008), each top-level eBay product category, each possible selling format (auction, pure fixed price, store item), seller feedback levels in 10 discrete bins, an item's final price in 10 discrete bins, the item's max{start price, reserve price} in 10 discrete bins, each possible scheduled listing duration in days (1, 3, 5, 7, 10, 30), each scheduled ending day of the week, whether an item is listed in bold typeface, whether an item is featured, whether the item's reserve price is different from its start price, and whether the item has a buy-it-now option. We also include continuous variables for: the number of photos and the log of the item's shipping fee. Standard errors are clustered at the seller level.
*** indicates significance at p = 0.01, ** for p = 0.05, and * for p = 0.10.

Appendix 1: Supplementary tables

This appendix provides table that supplement the data description and analyses in sections 4.1, 4.3, 5.1, and 5.4.

Table A1: Tests for correlation between charity status and other listing characteristics

Dependent variable	Constant	Charity	Charity × log(Feedback)
Reserve price	147.6***	0.0169	-0.0283
	(0.124)	(0.696)	(0.0773)
Shipping fee	6.321***	-0.267	0.0247
	(0.0552)	(0.242)	(0.0204)
Scheduled length	6.170***	-0.239	0.0478**
	(0.0453)	(0.184)	(0.0217)
Bold listing	0.0328***	0.00902	-0.00101
	(0.000826)	(0.00633)	(0.000756)
Featured	0.0156***	-0.00600	0.00111
	(0.00137)	(0.00772)	(0.00142)
Buy-it-now option	0.339***	0.0402	-0.00625
	(0.00350)	(0.0249)	(0.00431)
Photo count	1.243***	-0.00350	-0.000420
	(0.00275)	(0.0105)	(0.00118)

Notes**:** Each row includes results from a separate regression of an auction detail (e.g. reserve price) on a constant, a Giving Works indicator, and fixed effects for each seller-title-subtitle-start price combination. The standard errors, which are in parentheses, are clustered by seller. N = 162,505 with 22,610 groups. . *** indicates significance at p = 0.01, ** for p = 0.05, and * for p = 0.10.

Table A2: Listing characteristics of sellers who sometimes vs. never use Giving Works

Seller feedback level		Feedback 0-25		Feedback 26-100		Feedback 100-500		Feedback 500+	
Seller ever uses GW?		Yes	No	Yes	No	Yes	No	Yes	No
N sellers		5,190	830,898	4,626	829,155	5,321	776,032	3,149	406,842
N listings		138,090	9,408,064	145,551	11,045,556	296,039	24,466,355	959,090	100,863,195
Percentage GW		0.185	0	0.196	0	0.141	0	0.165	0
Start price	Median	8.99	7.75	8	7.49	7.99	6.95	9	7.99
	Mean	52.089	69.395	45.35	56.543	44.978	47.109	27.053	25.942
	Std. dev.	272.897	661.653	380.215	578.369	458.663	522.612	612.813	257.505
Shipping fee	Median	4.42	4.9	4.8	4.95	4	4.77	3.5	3.99
	Mean	5.538	6.225	5.576	6.244	4.846	5.917	4.264	4.973
	Std. dev.	11.914	18.393	8.402	13.294	8.439	13.289	6.65	8.796
Scheduled length	Mean	5.466	5.255	5.985	5.541	6.025	5.698	5.914	5.678
(Median = 7)	Std. dev.	2.498	2.502	2.153	2.235	2.013	2.109	2.041	2.16
Bold title (Yes = 1)	Mean	0.022	0.012	0.021	0.014	0.017	0.01	0.007	0.003
(Median = 0)	Std. dev.	0.148	0.109	0.144	0.117	0.129	0.101	0.082	0.059
Buy-it-now option (Yes = 1)	Mean	0.254	0.234	0.258	0.226	0.232	0.184	0.23	0.304
(Median = 0)	Std. dev.	0.435	0.424	0.437	0.418	0.422	0.387	0.421	0.46
Photo count	Mean	1.685	1.486	1.773	1.606	1.763	1.581	1.378	1.281
(Median = 1)	Std. dev.	1.725	1.425	1.793	1.592	1.793	1.597	1.401	1.147

Notes: These statistics are from all auction listings by US sellers during the second quarter of 2009. To save space, we omit statistics on "Featured," which all sellers used very rarely during 2009 Q2. Also, some listing characteristics (e.g. Scheduled length) have the same median value for both types of sellers in all feedback categories, so we report this median just once under the characteristic's name.

Table A3: Baseline effects of charity and other listing characteristics on auction outcomes

	(1)	(2)	(3)	(4)
Dependent Var.	Sold	# Bids	log(Price)	log(Maximum bid)
Charity	0.102***	0.265***	0.0380***	0.0402***
	(0.0159)	(0.0519)	(0.0108)	(0.0104)
Bold	0.0185	-0.102	0.0264	0.0374
	(0.0308)	(0.178)	(0.0278)	(0.0356)
Featured	0.0486	1.747***	0.126***	0.0972**
	(0.0504)	(0.580)	(0.0380)	(0.0392)
Ending Monday	0.0110	0.0610	0.0114	0.0157
	(0.0114)	(0.0401)	(0.0116)	(0.0101)
Ending Tuesday	0.00751	0.0575	0.00766	0.0170
	(0.00759)	(0.0359)	(0.00754)	(0.0116)
Ending Wednesday	-0.00557	0.0447	0.00464	0.0163
	(0.0112)	(0.0578)	(0.0111)	(0.0116)
Ending Thursday	0.00617	0.0731	0.0125*	0.0198**
	(0.00777)	(0.0459)	(0.00753)	(0.00939)
Ending Friday	0.00106	0.140	0.0195**	0.0269***
	(0.0115)	(0.0884)	(0.00810)	(0.00855)
Ending Saturday	-0.0176**	0.0132	0.0192*	0.0191*
	(0.00827)	(0.0372)	(0.0104)	(0.0110)
# of Pictures	0.0215*	0.244	0.0280	0.0222
	(0.0117)	(0.196)	(0.0219)	(0.0218)
Auction end date	-5.09e-05	-0.00255*	-0.000175***	-0.000273***
	(4.15e-05)	(0.00154)	(5.15e-05)	(3.41e-05)
Buy it now	0.0665***	-0.350***	-0.00841	-0.0610**
	(0.0218)	(0.0981)	(0.0280)	(0.0262)
Reserve difference	-0.0824*	-1.175***	0.0656***	-0.00124
	(0.0466)	(0.164)	(0.0171)	(0.00696)
(Reserve difference)^2	0.00206*	0.0280***	-0.00194***	-6.59e-05
	(0.00119)	(0.00467)	(0.000618)	(0.000255)
Shipping difference	-0.00270	-0.0480**	-0.00149	-0.00422
	(0.00318)	(0.0234)	(0.00345)	(0.00331)
(Shipping difference)^2	2.53e-05	1.35e-05**	-5.38e-08	2.19e-05
	(3.73e-05)	(6.58e-06)	(3.28e-05)	(3.54e-05)
Observations	104083	162766	54487	63841
R-squared (within)	0.014	0.014	0.007	0.008

Notes: We also include dummy variables for auction length (1, 3, 5, or 10+ days, with 7 as the excluded value), but do not report these estimates due to space constraints. *Ending* day is scheduled (not actual) ending day of week. *Reserve difference* is calculated as auction i's reserve price minus the minimum reserve price in i's group of matched auctions. *Shipping difference* is calculated similarly. Standard errors, clustered on seller, are in parentheses. *** indicates significance at $p = 0.01$, ** for $p = 0.05$, and * for $p = 0.10$.

Table A4: Seller feedback and charity's impact on bid count and sale price

	(1)	(2)	(3)	(4)
Dependent Var.	Bid Count	Bid Count	Log(Price)	Log(Price)
		Panel 1: Overall charity effect		
Charity	0.257***	0.713***	0.0380***	0.0964**
	(0.0514)	(0.161)	(0.0108)	(0.0412)
Charity		-0.0674***		-0.00803
× log(Feedback)		(0.0185)		(0.00493)
Observations	162,505	161,514	54416	54,177
R-squared (within)	0.014	0.014	0.007	0.007
		Panel 2: Effects by donation share		
Donation=10%	0.105***	0.242**	0.0215**	0.0351
	(0.0367)	(0.0954)	(0.0103)	(0.0280)
Donation=10%		-0.0181*		-0.00175
× log(Feedback)		(0.00968)		(0.00371)
10%<Donation<100%	0.287***	0.438***	0.0354*	0.0919
	(0.0552)	(0.148)	(0.0211)	(0.0562)
10%<Donation<100%		-0.0271		-0.00855
× log(Feedback)		(0.0218)		(0.00823)
Donation=100%	0.393***	1.482***	0.0638***	0.208*
	(0.107)	(0.384)	(0.0238)	(0.107)
Donation=100%		-0.170***		-0.0226
× log(Feedback)		(0.0510)		(0.0147)
Observations	162,505	161,514	54416	54,177
R-squared (within)	0.014	0.015	0.007	0.008

Notes: Standard errors, clustered on seller, are in parentheses. *** indicates significance at p = 0.01, ** for p = 0.05, and * for p = 0.10. See Table 2 for additional notes.

Appendix 2: Calculating the profitability of electing a 10% Giving Works listing

Suppose a seller has an item to sell on eBay. The cost of obtaining the item is sunk, so we ignore it here. The seller has two auction formats (j) available: Giving Works (d) and non-Giving Works (nd). Let q^j represent the probability of the item selling under format j during period (week) 0, when the item is first listed. Let p^j be the expected price of the item under format j during period 0, conditional on the item selling. If the item fails to sell during a listing period, the seller can re-list it and attempt to sell it again during the next period. Future periods are discounted at rate β. The price in period t is expected to be $p^j(\delta_p)^t$, where $\boldsymbol{\delta}_p$ is the weekly decline in the item's price and t is an exponent. The per-period sales probability declines at rate $\boldsymbol{\delta}_s$. We consider the value of selling the item under two strategies. First, the seller may commit to selling the item outside of GW, and relist the item as many times as necessary until it sells. Second, the seller may commit to using GW to list the item until it sells, with a pledged donation of η. The present discounted values of these two strategies are U^{nd} and U^d, respectively. We do not allow the seller to switch between formats d and nd or consider changing η, and we effectively assume that the reserve price is invariant to the selling strategy so that we can use our empirical results to predict the impact of a strategy on q^j and p^j. The values U^j include eBay's listing fees, which are dependent on whether an item sells and its price conditional on selling. Let k denote the component of listing fees that are independent of whether an item sells, and let f be the additional fee conditional on an item selling. (We describe the eBay fee structure and levels that prevailed at the end of our sample period.) Under Giving Works, the seller is responsible to pay only $(1-\eta)$ of k and f. We note further that eBay uses a two-part tariff for final value fees. Below \$25, denote the marginal final value fee as f_1 and above \$25 denote it as f_2.

When the final price is above \$25 and neither price nor sales probability decline over time, the PDV of selling an item under format *nd* may be written recursively as:

$$U^{nd} = q^{nd}[p^{nd} - f_2(p^{nd} - 25) - f_1 25] - k + (1 - q^{nd})\beta U^{nd}, \quad \text{or}$$

$$U^{nd} = \frac{q^{nd}[p^{nd} - f_2(p^{nd} - 25) - f_1 25)] - k}{[1 - (1 - q^{nd})\beta]}.$$

When the final price is less than \$25 and p^{nd} and q^{nd} are constant, the PDV of selling an item under format *nd* is:

$$U^{nd} = \frac{q^{nd}p^{nd}(1 - f_1) - k}{[1 - (1 - q^{nd})\beta]}.$$

If p^{nd} and q^{nd} can change over time, then U^{nd} is complicated slightly by the interaction of eBay fees with the price decline, but the expression remains easy to evaluate numerically. This is the approach we follow in Table A5.

When the seller follows the GW strategy in auctions with constant expected prices and sales probabilities, the recursive expressions above may be extended to include the donation parameter η. For a final price above \$25, the PDV of selling an item under format *d* is:

$$U^d = q^d\left[(1 - \eta)\left(p^d - f_2(p^d - 25) - f_1(25)\right)\right] - (1 - \eta)k + (1 - q^d)\beta U^d, \quad \text{or}$$

$$U^d = \frac{q^d\left[(1 - \eta)\left(p^d - f_2(p^d - 25) - f_1(25)\right)\right] - (1 - \eta)k}{[1 - (1 - q^d)\beta]}.$$

When price is below \$25 but all other assumptions remain fixed, the PDV of selling an item while pledging a 10% donation is:

$$U^d = \frac{q^d[(1-\eta)(1-f_1)p^d] - (1-\eta)k}{[1-(1-q^d)\beta]}.$$

As in the non-GW selling strategy, we evaluate U^d numerically to accommodate weekly changes in sales price and probability.

Table A5: The present value of revenue from charity versus non-charity selling strategies

	No Donation	Average Effect Across Sample	25th percentile Seller Feedback	50th percentile Seller Feedback	75th percentile Seller Feedback	Max Seller Feedback
10% donation impact on						
Sale probability	--	5.85%	11.97%	9.82%	8.08%	0.52%
Sale price	--	2.15%	2.91%	2.64%	2.41%	1.44%
Expected Revenue, Single Sale						
At median start price	33.63	31.56	32.25	32.02	31.83	30.82
		93.9%	*95.9%*	*95.2%*	*94.6%*	*91.7%*
At mean start price	71.76	67.70	69.36	68.82	68.34	65.01
		94.3%	*96.6%*	*95.9%*	*95.2%*	*91.7%*
Mean Time to Sell (days)						
At median start price	23.6	19.7	16.8	17.8	18.5	23.2
		83.4%	*71.2%*	*75.4%*	*78.4%*	*98.3%*
At mean start price	28.2	22.8	19.0	20.2	21.3	27.6
		80.8%	*67.4%*	*71.6%*	*75.5%*	*97.8%*

Notes: To determine the 25th, 50th, and 75th percentiles, we calculate each seller's average feedback within a SPSE match and sort the 22,610 match-level average feedback values. These figures are 30, 146, and 526, respectively. The maximum average seller feedback in our sample is 136,297.4. Median and mean start prices for 10% donations are 39.99 and 84.83, respectively. Calculation assumes an annual cost of capital / discount rate of 10%, a daily price decline of .015%, a daily sale probability decline of .005%, and listing and final value fees at eBay as of 10/6/2009, including a 10% rebate in listing fees for 10% donations. We assume no use of listing options, such as extra photographs, bold listings, or buy-it-now prices that require extra listing fees. Doubling the discount rate, the daily price decline, and the daily sale probability decline (all simultaneously) change the calculated present value by less than 1%. Because a majority of listings in our SPSE sample come from high-feedback sellers, the average affect across the sample is smaller than the average effect for a seller with the 75th percentile average feedback level.