Reputation, altruism, and the benefits of seller charity in an online marketplace*

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Abstract

We analyze "natural experiments" on eBay where sellers offer identical products with and without charity donations. Charity-tied products are more likely to sell and attract higher prices, and these benefits accrue primarily to sellers without extensive eBay histories. This suggests that consumers view charity as a signal of seller quality and a substitute for reputation. We also find that charity-tied products by all sellers are more likely to sell (and at higher prices) immediately following Hurricane Katrina, implying that consumers derive direct utility from seller charity at times when charity is particularly salient.

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1. Introduction

Many for-profit corporations contribute to public goods via charitable donations.[1] There are several views on what motivates these contributions, which seem to conflict, at least superficially, with profit motives. First, some group relevant to the firm – employees, consumers, or regulators – may value "charity for charity's sake."[2] As a result these constituencies may, respectively, take lower wages, pay higher prices, or pass supportive legislation for generous companies.[3] In this view, a firm's charitable giving could result in higher profits. A second view argues that support of public goods may result from owner or managerial preferences unrelated to profit maximization, potentially involving misgovernance as famously argued by Milton Friedman (1970). A third, intermediate position holds that – particularly in cases of asymmetric information or where there exists the potential for opportunistic behavior – firms may use charity as a credible signal of quality or reliability (Fisman, Heal, and Nair, 2006). This signaling view requires that less opportunistic managers also be those who derive greater utility from charitable giving or other contributions to public goods. Consumers, in turn, then interpret charitable giving as a signal of the firm or manager's trustworthiness or quality.

In this paper, we assess the evidence on how consumers respond to charitable giving by firms—both "charity for charity's sake" and signaling—by looking at sellers'

[1] See, for example, McKinsey (2008).

[2] We use this expression to refer to charity entering a person's utility function. There are several reasons why this might occur. Individuals may value the well-being of others (altruism) or they may derive pleasure from the act of giving, what Andreoni (1989) termed warm glow. Our paper does not distinguish among these explanations, but rather attempts to distinguish between the direct utility of charity and reputational benefits.

[3] A growing theoretical literature, exemplified by Bagnoli and Watts (2003) and Baron (2007, 2009), seeks to explain the adoption by firms of socially responsible practices when various decision-makers value the charitable output of these practices.

outcomes in charity and non-charity auctions on eBay. The charity auctions we study are made through eBay's Giving Works (GW) program, which allows sellers to direct a fraction of an auction's proceeds (between 10 and 100 percent) to a charity of their choice. We utilize a new dataset that provides information – quarter by quarter – on the *universe* of items placed on eBay by any seller who initiates at least one GW auction in that quarter. For our sample period of January 2005 to March 2008, we observe a total of 23.5 million auctions across 78,000 distinct sellers. This includes a wide range of activities, including benefit auctions by non-profit sellers, for-profit sellers using eBay for occasional philanthropy, for-profit sellers that regularly make small donations (perhaps as part of a marketing strategy), and sellers that appear to experiment deliberately with the GW option. In many cases listings with *identical* titles, subtitles, start prices, and other auction attributes were listed by the same seller, often only a few days apart. The only observable difference, both to us and also to potential bidders, was the listing's charity component. We argue that this effectively presents a dataset of many thousands of natural experiments performed by eBay sellers that allows us to infer the value placed on charitable giving by consumers.

Using a sample of over 150,000 auctions matched by seller, title, subtitle, and start price (extracted from our original sample of over 23 million auctions) we find a modest premium associated with GW auctions. This ranges from a 6 percentage point higher sale probability and 2 percent higher sale price (conditional on selling) for auctions where 10 percent of the proceeds went to charity, to increases in sale probability and price of 13 percentage points and 6 percent, respectively, for 100 percent charity auctions. This

empirical result is robust to a broad range of additional controls and to matching based on an even more refined set of listing attributes.

We further attempt to distinguish whether the GW premium is due primarily to consumers valuing "charity for charity's sake" or their inferring a quality signal from the charity commitment. In deciding whether to bid on a product, an eBay consumer must consider whether the item and its delivery will match the seller's descriptions. When consumers anticipate that some sellers will fail to provide satisfactory service, trade can slow or break down, as in Akerlof (1970). This challenge is exacerbated by problems the online marketplace has had with seller misrepresentation over the years.[4] One obvious indicator of a seller's expected quality or reliability is consistently positive feedback, which has been shown to have a significant impact on auction outcomes (see Houser and Wooders, 2006; Cabral and Hortacsu, 2010). We argue that a charity tie-in may serve as a substitute for a history of positive feedback in the minds of consumers, thereby benefitting inexperienced sellers.[5]

The intuition for charitable giving as a credible quality signal is straightforward and premised on the assumption that there are some sellers who care only about profits and others who care about profits as well as their impact on others. Fisman et al. (2006) provide a formal model of sellers who separate by charitable giving. For purely profit-minded sellers, charity is more "expensive" since they do not derive psychic benefits from charitable giving. Other sellers, however, receive utility from donating to charity

[4] For example, an audit conducted by Tiffany found that 73 percent of its silver jewelry listed on eBay were counterfeits (See "Tiffany and eBay in Fight over Fakes," *New York Times* November 27, 2007). See also Jin and Kato (2006), who find that baseball card quality is frequently misrepresented on eBay.

[5] There are obviously other means of influencing consumers' quality inferences. Roberts (2009), for example, presents evidence that warranties can be an effective substitute for seller reputation.

and also suffer a psychic penalty when they act opportunistically with respect to consumers, for example by providing a lower quality product than advertised. Under these assumptions, charitable tie-ins can act as a credible signal of product quality.[6]

If consumers believe that charity tie-ins are a useful indicator of seller reliability, we argue that the signal value should be greater for sellers whose quality is most uncertain. On eBay, these are the sellers who lack a long history of positive customer feedback. We find that the sale probability and price premiums associated with GW auctions are concentrated among low-feedback sellers, in particular those in the lowest quartile of feedback within our sample. For this subset of sellers, GW auctions are associated with a 12 percentage point higher sale probability for 10 percent charity auctions, and as much as a 54 percentage point increase in sale probability for 100 percent auctions. Additionally, for low-feedback sellers GW auctions have 4 percent to 25 percent higher sale prices for 10 and 100 percent charity auctions, respectively. For sellers in the highest feedback quartile the impact of GW is small. We find that this relationship between GW impact and seller feedback is robust to a range of alternative specifications. Consumers may have limited responses to charity by high-feedback sellers because GW status does not add significant information about these sellers' quality. By contrast, at low feedback levels much less seller-specific information is available, so consumers see GW status as a powerful signal about seller type.

The magnitudes of our results suggest that 10 percent GW auctions do not yield

[6] Prior research has in fact found a correlation between measures of corporate citizenship and consumer trust (see, for example, Pivato et al., (2008)) but these correlations have problems of causality. Similarly, Siegel and Vitaliano (2007) assume that socially responsible activity makes consumers more likely to find a firm trustworthy, and find that firms selling experience goods are more likely to invest in socially responsible practices than those selling search goods.

benefits that compensate for the revenue that goes to the charity.[7] Back-of-the-envelope calculations using our point estimates for increases in sale probability and final sale price indicate that low-feedback sellers exclusively using 10 percent GW auctions receive, in expectation, 96% of the present value of net revenue (accounting for listing fees and donations) that they would have received had they auctioned their products outside the GW program. Thus, even for low feedback sellers the incremental returns are below the level required to offset the cost of donations.[8] Therefore choosing to donate can plausibly separate purely profit-maximizing sellers from those with other-regarding social preferences. While our results suggest that opportunistic sellers will not, on average, increase profit by using GW, in this paper we are agnostic about sellers' motivations for making charitable donations, including those we observe as "experiments." During the period we investigate, the Giving Works program was relatively new, and reliable estimates of the program's benefits were difficult to obtain by sellers.

Finally, in an extension, we examine whether variation in perceived charity need affects consumers' willingness to pay for charity-linked auctions. We look at the holiday buying season (post-Thanksgiving to New Year's), and also the period following Hurricane Katrina in 2005, which triggered a surge in charitable giving nationwide (Center on Philanthropy at University of Indiana, 2006). We find that the average GW premium increases for all donation levels in the months following Katrina. Further, the GW premium rises by a comparable amount for all levels of seller feedback, suggesting that in

[7] We also confirm that this is the case for higher donation levels.

[8] These same calculations show, however, that GivingWorks is an efficient way for sellers to pursue existing altruistic goals.

periods of heightened awareness of charity, altruistic and/or warm glow motives may be more prevalent. By contrast, we do not find any differential effect of the holiday period on the GW premium.[9]

There exists some prior research on the impact of charity, and corporate good works more broadly, on consumers' willingness to pay. Closest to our work is Elfenbein and McManus (2010), who examine 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. They find evidence of a positive price premium that increases with the fraction of proceeds donated to charity and declines with the value of the underlying item for sale. The current paper improves upon that work in several ways. First, we are able to analyze the universe of GW auctions rather than a hand-drawn extract, which enables us to look across a broader range of products and to examine naturally occurring seller experiments in the marketplace. This, in turn, allows us to control for unobserved seller heterogeneity, the effects of which could not be ruled out in the prior work. Second, since eBay has provided us with all GW listings and not just completed sales, we are able to examine the impact of GW on both price and sale probability, whereas Elfenbein and McManus (2010) are only able to look at the price differences, conditional on the product being sold. Third, and most importantly, the richness of our data allow us to examine differing theories on the source of seller benefits from charity tie-ins.

Most other work examining the benefits of firms' good deeds has relied on firm-level, cross-sectional studies, for example observing that companies with strong

[9] Note that this is consistent with the patterns reported by Levitt (2006) in his study of non-payment for bagels during Christmas, which he attributes to the economic stresses of this period.

corporate citizenship earn higher profits, but these analyses are fraught with problems of causation (see Margolis and Walsh (2003) and Margolis, Elfenbein, and Walsh (2007) for reviews of this literature). Exceptions include Hiscox and Smyth's (2008) experimental evaluation of how "fair labor" sourcing affects demand, and Casadesus-Masanell et al.'s (2009) study on Patagonia's introduction of organic cotton to its clothing products. These studies find a strong effect of corporate good works on willingness to pay. In neither case, however, can the authors distinguish amongst the possible reasons for the effect, and potentially conflate the separate effects of corporate citizenship and marketing.

More broadly, our work also builds on prior research that examines the relationship among altruism, reputation, and quality. List (2006), for example, finds that baseball card sellers exhibit non-selfish behavior in market transactions only when long-term commercial relationships are possible, despite the fact that sellers with and without potential future business behave altruistically in lab experiments. McManus and Bennet (2009) find that consumers spend more at a nonprofit organization's online store when their purchases may trigger additional donations by an anonymous donor, and they argue that improved perception of the nonprofit's products explains much of the increase in demand.

2. 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 2007, and currently the site has 88.4 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 addition details on eBay and the practices within it, see the survey article by Bajari and Hortascu (2004).

eBay employs several mechanisms to facilitate trade. eBay's PayPal system provides a single, secure platform for users to send payments in a variety of currencies. To monitor seller quality, eBay maintains a feedback system. New users begin with a feedback score of zero, and sellers or buyers with whom they have completed transactions 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.[10] Consumers may obtain additional information about seller quality by browsing comments left by other users, or reviewing the seller's performance in a small group of measures (e.g. item as described, shipping time) for which eBay began tallying ratings in 2007. During the period of our study, eBay also provided a "power seller" designation (a small symbol next to the seller's name) for high-volume sellers who met minimum customer satisfaction criteria; virtually all high feedback sellers had power seller status during this period.

In 2003 eBay introduced the Giving Works (GW) 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 non-profit 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 listing's 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 about 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

[10] In Elfenbein and McManus (2010), for example, the median percentage of positive feedback is 99.8%.

seller will follow through on a donation pledge.

Sellers who use GW receive two immediate and concrete benefits from the program. First, sellers can claim the entire donated sum as a tax-deducible 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 listing fees equal to the percentage donated to charity.

Figure 1 displays quarterly statistics on GW activity for US-based items by donation level 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. During these three quarters, the number of 100% donation listings increased steadily. 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 Hurricane Katrina, but otherwise exhibits an upward trend that mirrors the growth of GW listings. With the exception of the Katrina period—during which an average of 6 products were listed on GW for each seller—the sellers who used GW created 20 charity listings per quarter on average. The number of

listings per GW user per quarter exhibited a slight increase over the period for which we have data, rising from 15 in 2004 to 23 in 2007.

2.1 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 listings among all GW listings, or to look for those associated with a particular non-profit. In these cases, consumers generally do not see non-GW listings of similar products. Third, consumers may encounter special GW promotions from the eBay's front page. These promotions are usually focused on a charitable cause or nonprofit organization rather than a product.

Although there is a wealth of information about products and sellers on eBay, prior evidence 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 (2009) show that (some) eBay bidders win auctions at prices higher than contemporary 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 interpret this as bidders failing 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 prior 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. This is particularly challenging in the case of prior donations made by a seller, as uncovering this is at best time-consuming and at worst impossible.[11] Overall, this literature suggests that any quality inferences by consumers from charity commitments would be derived mainly from the presence or absence of a GW donation in the listing of interest, rather than a general seller-level quality inference formed by examining the complete history of the seller's giving behavior. This characterization of consumer search supports our approach of focusing on the direct benefits of a charity-linked listing, rather than the spillover benefits to a seller's other listings.

3. Data

3.1 Constructing the sample

eBay provided us with a custom extract of 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, which includes 23.5 million listings, we identified "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

[11] During our period of study, eBay did not make the cumulative donations of a seller available to potential bidders.

particular, we are interested in experiments that exhibit variation in the share of revenue donated to charity.

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.[12] 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 experiments that lack variation in the 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

[12] Including the data from 2004 would add fewer than 2,000 observations (1.2%) to the sample we analyze.

same seller, title, subtitle, and start price.

For each observation in the SPSE sample, we utilize data on several auction characteristics that are 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 bidders' search results; an indicator for whether a stock-keeping unit (SKU) was provided;[13] the number of photos included on the listing page, top-coded at 8; and the item's eBay product category designation, which may include up to six distinct hierarchical descriptions that range from a general category (e.g. "Consumer Electronics") to a narrow set of products (e.g. "iPod Shuffle"). In addition, for each auction we observe the following variables which 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 an 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 several characteristics of the seller: the seller's feedback rating at the beginning of each auction; the date that the seller created his eBay account (used to calculate the seller's "age" at the auction's start date); and the seller's home city and state. As the convention among eBay users is to provide a single unit of positive feedback for each transaction, and more than 99% of feedback

[13] eBay allows sellers to provide a SKU for a product at no cost. We take the presence of a SKU to indicate that the product for sale meets well-known, verifiable, specifications, and hence that opportunities to misrepresent the product are minimized.

ratings are positive, the seller's feedback score is essentially proportional to the number of transactions he has conducted on eBay, with equal weight given to purchases and sales.

In assembling and analyzing the SPSE sample, we assume that products within a match are identical. This data collection process is likely to lead to under-matching in which we fail to capture identical products that have different titles. For example, a seller might add the phrase "donation to the Red Cross" to a listing's subtitle for otherwise identical products and listings, but we exclude the affected observations from our analysis. Although under-matching reduces our sample size, we do not expect these omitted observations to introduce bias to our analysis. Our matching rule also may suffer from over-matching, in which a seller assigns the same title, subtitle, and start price to products which actually differ. If Giving Works status is correlated with characteristics which we do not observe but are apparent to sellers and bidders, our estimates of charity impact could be biased. However, in Appendix Table A1, we present regression results which indicate that observable within-match variation in other listing characteristics is uncorrelated with GW status. Further, when we limit the sample to experiments that match on many seller-selected characteristics, we find that our results are largely unchanged. Hence, it is unlikely that unobserved variability from selection into GW is behind our results.

The experiments we analyze are a small fraction of sellers' GW activity. Between January 2004 and March 2008 we observe 78,037 unique sellers with at least one GW listing. Our sample contains 23.5 million eBay listings, of which 2.1 million are GW items. About 5,600 sellers acted as non-profits and always donated all of their revenue, but these sellers account for only 150,000 listings. Thus the bulk of GW activity is by

sellers who attempt to profit from their sales (at least sometimes) and also do not engage in experiments, as we define them here.[14] In this paper, we take no stand on whether the "experiments" we observe are examples of sellers trying to learn about GW's benefits or are, instead, cases in which sellers' philanthropic motives lead them to use GW for some portion of their eBay activity. Rather, we exploit this experimental variation to assess consumer response to GW.

Among for-profit sellers who use GW, charity listings are about 9% of all eBay activity. The share is slightly lower among the 3,062 sellers who appear more than 1,000 times in the full data. In 73% of GW listings by for-profit sellers, 100% of revenue is pledged to charity, and an additional 18% of listings pledge 10% of revenue. 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. (Alternatively, it is also consistent with sellers learning that charity auctions do not generate positive returns.)

3.2 Summary statistics

In Tables 1-3 we present summary statistics from the SPSE sample. Table 1 contains information on the 5,015 unique sellers in the data. Sellers average 4.5 distinct

[14] Recall that our sample of experimental sellers comprised 5,015 sellers and 162,505 listings. If we were to expand the matched data to include listings in non-auction formats and without the restriction that start prices are identical, we would add only 4,841 additional sellers and 127,000 listings.

title-subtitle-start price combinations and 32.4 listings in total. About 30 sellers account for nearly half of the SPSE data, so the median numbers of matches and listings are considerably smaller. 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 4, we allow for changes over time in sellers' feedback over the sample period, 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 categories and 2.6 categories at the next level in the hierarchy.

In Table 2 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. However, larger matches tend to have a relatively high fraction of charity listings so that overall we observe more GW listings than non-GW. A small fraction of matches (2.8%) include variation in reserve price, and a small additional number (1.9%) have a uniform reserve that is greater than the posted starting price. Shipping fees vary in a relatively large share (12.5%) of matches, but the median standard deviation of shipping fees ($0.87) within an experiment with any variation is small relative to the median ($4.99). Within-match variation is rare for bold status, featured status, or the presence of a SKU, with each varying in about 2% of matches. Photo counts and the presence of a buy-it-now option are more likely to vary within a match (4.9% and 8.7%, respectively). In many cases, there is within-match variation in multiple attributes so that

73% of all matches have no variation in any of the variables mentioned above. Auction length, however, varies relatively frequently within a match: 28% of matches include some variation in scheduled duration.

Table 3 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). With our sample of 162,505 listings, this implies total revenue of $4.2 million. While only 5% of matches include observations with a secret reserve above the start price, the frequency of this choice among high-volume sellers yields distinct reserve and start prices in 39% of the SPSE listings. For each non-charity item within a match, we computed the minimum number of days between its own start date and the nearest start date for a GW item in the same SPSE match. The average across minimum differences is 48 days, and the median is 21 days. While the modal auction length of seven days implies that side-by-side comparisons of matched GW and non-charity listings were often impossible, 26% of the non-charity listings have a minimum difference of 7 days or fewer. Within the GW auctions, 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. Overall, this suggests that for most sellers, the "natural experiments" we observe are not, in general, created by sellers who are using these matched listings to learn about the profitability of GW sales in a systematic way.

There is relatively little within-seller variation in positive donation rates – 20 percent of the GW listings in our final dataset come from sellers with only 10 percent

donation levels, and an additional 61 percent come from sellers with exclusively 100 percent donations. For the subset of 10-percent-only sellers, it is possible that the primary purpose of experimentation is to learn about the GW premium.[15]

4. Results

Our analysis proceeds in four parts. We begin by estimating the average impact of charitable donations across the SPSE sample. Next we examine the heterogeneity of the charity impact across sellers with different levels of experience to explore whether charity tie-ins may provide credible signals to consumers about seller quality. Third, we explore whether charity tie-ins can lead to higher profits. Finally, we compare the charity impact immediately following Hurricane Katrina and also during the holiday season to the charity impact at other times to examine the degree to which the charity premiums may be driven by consumers who value "charity for charity's sake."

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

$$Y_{ism} = \alpha_{sm} + \beta' DONATION_{ism} + \theta' CONTROLS_{ism} + \varepsilon_{ism} \qquad (1)$$

where s indexes the seller, m represents a title-subtitle-start-price matched group of listings, and i is a subindex within each group for a specific listing; α is a fixed-effect by group and seller. We explore consumer responses to charity tie-ins by examining four different dependent variables (Y): the probability of sale, the number of bids submitted at or above

[15] It is possible that 100 percent sellers expect to augment their reputations through GW listings. However, given the limited ability of buyers to observe past charitable behavior, we believe that 100 percent GW listings by for-profit sellers most likely represent an efficient means of making a (private) charitable donation. For our purposes, these auctions are nonetheless useful for understanding consumer response to seller charity.

the starting price, the natural log of the ending price of the auction if the product did sell,[16] and the natural log of the maximum bid submitted by any bidder. The variables included in *DONATION* reflect the presence and levels of charitable donations via GW, and vary by specification. *CONTROLS* includes indicator variables for use of bold titles and featured status in the item listing; indicators for the scheduled length of the listing and day of the week on which the listing was expected to close; the number of pictures provided in the listing; an indicator variable reflecting whether "buy-it-now" was an option; controls for differences in shipping and reserve prices across items in the match;[17] and the scheduled end date of the auction, which allows us to control for time trends in demand for identical items on the site. In all of the analyses that follow, we report standard errors clustered by seller since the main variation of interest is at the seller level. Additionally, this approach helps account for the widely varying numbers of listings by seller in our dataset.[18]

4.1 The average charity impact

We report the average impact of charity in Table 4, using a binary variable that equals one if any amount is donated to charity and zero otherwise. Column (1) reports the impact of charity tie-ins on the probability of sale using a linear probability model. The linear model facilitates interpretation of the marginal effects of charity, and generates very similar results to a conditional fixed effects logit model. As with a fixed effects logit

[16] If there is only one bidder, this value is equal to the starting price, otherwise it reflect the second-highest bidders' bid.

[17] 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.

[18] We also find in unreported results that dropping sellers with large numbers of SPSE listings has little impact on our point estimates.

specification, we omit observations where either none or all of the listings within a group result in sales.[19]

We find that 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 percent, this represents a 30 percent increase in the likelihood of making a sale. In the remaining columns, we present different measures of consumers' responses to charity status. In column (2) we see that GW auctions attract on average 0.26 more bids, and columns (3) and (4) indicate that there is a 4 percent sales price premium associated with GW auctions, conditional on a sale taking place. None of the controls have a consistently significant sign, apart from *Featured*, which has a positive impact on sale probability and price.

In Table 5, we incorporate variables in *DONATION* that reflect the fractions of total item revenue that will be donated to charity. As expected, sale probability, number of bids, log of price, and log of highest bid all increase monotonically in the donation rate. These results indicate that, for otherwise near-identical auctions, greater charitable contributions are more likely to lead to sales and elicit higher selling prices. The coefficients reported here are comparable to those reported by Elfenbein and McManus (2010).

4.2 Heterogeneity of charity impact by seller experience

As discussed in the introduction, there are two primary explanations for consumers'

[19] If we keep these observations, the implied effect of GW is – as would be expected – somewhat lower, given the likely bias towards zero of all coefficients. Our main results remain qualitatively (and statistically) similar; tables utilizing this larger sample are available from the authors.

higher willingness to pay for charity-linked products – direct utility from donating to the charity itself, or because they believe that the charity-linked product is somehow of higher quality. The quality signaling story suggests that the benefits of GW should be lower for sellers with an alternate means of demonstrating quality. A natural alternative in the case of eBay is feedback from customers. We therefore examine how GW's effect on sales probability and the log of the maximum bid varies with seller feedback. We use the highest bid (rather than price) because the bid value always reflects a bidder's choice, whereas auctions with a single bid will close with a price that reflects the seller's choice of starting price.

In Table 6, we repeat the analysis in Table 4, adding the interaction term *Charity**log(*Feedback*) and also a set of interactions by *Feedback* quartile.[20] In all cases, these interaction terms take on negative values and are significant at the 1 percent level, indicating a lower GW premium for higher-feedback sellers.[21] In columns (2) and (4), the specifications based on feedback quartiles, we see that for the lowest quartile of seller feedback, the increase in sale probability associated with GW auctions is 38.5 percentage points, and the increase in maximum bid is 17 percent. The coefficients describe a monotonic decrease in the GW premium as a function of seller feedback, with premiums of 5.4 percentage points on sales probability and 1.6 percent on bids for the highest quartile.[22] Table 7 once again allows for a differential effect by donation level, with a full set of

[20] The feedback cutoffs between quartiles are 30, 146.5, and 526.2.

[21] We also estimated specifications (1) and (3) of Table 6 while restricting the SPSE sample to the observations that have no within-match variation in bold, featured, number of photos, buy-it-now option, secret reserve price, or shipping cost. The implied effect of charity (and its interaction with feedback) are similar to that of the full sample

[22] 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.

interactions between donation share and feedback measures. In all cases, the benefits of a charity tie-in are diminished for higher feedback sellers.

In Table 8 we present a set of robustness checks. First, we examine whether seller feedback might be proxying for the prevalence of "commodity" auctions. If there is less scope for opportunistic behavior in commodity sales, then there would be less potential for quality signaling for such products. Our proxy for commodity auctions is whether the item for sale has an SKU associated with it, and we look at whether the inclusion of *Charity*SKU* affects our main results on seller feedback. The results, in columns (1) and (2), imply relatively little difference by SKU status, and our results on feedback are unchanged by the inclusion of the SKU controls.

Columns (3) and (4) include seller age as a control, interacted with *Charity*. Surprisingly, given the colinearity of age and feedback, our main results are unchanged. The coefficients on the log(*Seller age*) terms are small and only marginally significant. We display the results of further robustness tests in columns (5) through (10). We interact *Charity* with seller category concentration,[23] item start price, and a full set of dummy variables for the seller's home state. These controls similarly have little effect on our main results.[24] In summary, our results indicate that GW auctions generate the greatest seller benefits for low feedback sellers. We argue that this is because charity tie-ins substitute for seller feedback and are seen by buyers as a credible quality signal.

[23] We calculate the share of a seller's listings in the full data that occur within the same top-level product category as the SPSE observations.

[24] We also repeated our analyses limiting ourselves to the set of GW listings that do not overlap with their matched non-GW listings. We obtain virtually identical results, which helps to rule out the possibility of reputational spillovers across auctions. It also is inconsistent with the feedback-charity interaction resulting from high-feedback sellers simply being those with many simultaneous auctions, where the GW premium is attenuated because of cross-listing reputational spillovers.

4.3 Are charity tie-ins directly profitable?

For charity links to act as informative signals of seller quality, it must be the case that opportunistic sellers are not tempted to use charity links to boost profits.[25] The basic condition is that the financial benefit to a seller from higher sale probabilities and prices cannot exceed the cost of donating. We compare selling strategies in which a seller commits to offering an item via GW until it sells or outside of GW until it sells. If the expected non-charity price of an item is p_n, conditional on selling, the probability of a non-charity sale is π_n, and β is the per-listing-period discount rate, then the present discounted value of revenue from committing to non-charity listings is $V_n = \pi_n p_n + (1-\pi_n)\beta V_n$. The discounted revenue value from a GW listing (g), which may have a different sale probability and price, is $V_g = \pi_g (1-\gamma) p_g + (1-\pi_g)\beta V_g$, where γ is the fraction of revenue donated to charity. In the Appendix 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 which we report in Table 3. 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. In Table A2 we explore the expected value of pursuing a GW selling strategy using 10% donations and compare it to the expected value of the non-GW selling strategy. In our calculations we employ the predicted price premium for 10% GW listings, which we report separately in Table A3. This analysis shows that 10% donations do not provide a greater present value

[25] 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 tax benefits of GW sales.

net of fees and donations than committing to non-GW listings. On average across the sample, pursuing a 10% donation strategy to sell an item yields 93.9% of the net discounted revenue of selling via a non-GW strategy. Even for low-feedback sellers, the benefits of pursuing a 10% donation strategy yields 95.9% of the discounted revenue of a non-GW strategy.[26] For low-feedback sellers, the greater benefit of 10% donations may be that they allow items to be sold sooner (i.e. with fewer re-listings), which allows positive feedback to accumulate more quickly. One caveat to this analysis is that starting prices across GW and non-GW auctions, which are identical in our SPSE sample, may not be equal if each is set to maximize seller profit.

4.4 Variation in the salience of charitable giving

The results above suggest that charity pledges have a substantial impact on sale probabilities and bids in auctions by low-feedback sellers, but consumers have only a modest response to Giving Works listings by high-feedback sellers. This is largely consistent with a view that consumers infer a quality signal from seller charity, but derive relatively limited direct utility from charity-linked purchases. We now ask whether the data are ever consistent with consumers deriving substantial utility benefits from charity sales. To answer this question, we examine whether events that draw attention to worthy causes affect the sale probabilities and price premiums associated with Giving Works. We focus on the aftermath of Hurricane Katrina, which made landfall on August 30, 2005 and spurred a period of near-record giving by Americans who rushed to donate to relief efforts.

[26] See the notes below Table A2 for the numerical assumptions for these calculations.

We define the post-Katrina period as September 1 to November 30, 2005, and we add *Katrina Era* and the interaction *Charity*Katrina Era* to the basic models we described in Table 4.[27] Consistent with an increased focus on charitable causes following Katrina, we find that GW listings received an additional 9.7 percentage point increase in sales probability. In columns (3) and (4) we limit the sample to sellers with above-median feedback and show that their Katrina-era gains in GW sale probability and maximum bid are substantial, which is consistent with the Katrina effect acting through feelings of altruism and/or warm glow among customers. In columns (5) and (6) we show that the Katrina-era changes to sale probability and maximum bid were concentrated among the nonprofit organizations specifically associated with hurricane relief efforts.[28] Listings associated with relief-oriented charities experienced a 16 percentage point increase in sale probability relative to their baseline charity premium, while GW listings not associated with hurricane relief performed equally well within and outside of the Katrina era.[29]

Finally, in columns (7) and (8) we examine whether there is an annual increase in charity appeal during the period between Thanksgiving and New Year's Eve. We create a *Holidays* dummy variable to denote listings which started on Thanksgiving or later and ended on New Year's Eve or earlier, and we interact this variable with the indicator *Charity*. In contrast to the Katrina results, we do not find any change in the GW premium in this

[27] The variable *Katrina Era* is identified by variation within a match in whether listings occur during the months following Katrina.

[28] Following Hurricane Katrina, the federal government identified 93 charities as approved relief organizations (www.opm.gov/cfc/disasters/Katrina-relief.asp). We identified these charities, their local chapters, plus all other hurricane- or gulf coast-related groups as being associated with Katrina relief.

[29] It is noteworthy that Katrina charities command smaller premiums outside of the post-Katrina period. This pattern holds for all donation levels. We do not have an adequate explanation for this result, but hope to explore it in further work that delves more deeply into heterogeneity in GW by charity type.

period.[30] Overall, these results suggest that charity links generate widespread consumer responses only when consumers perceive the charitable need as unusually large.

5. Conclusions

This paper is among the first to consider what types of firms can influence consumer behavior through charitable contributions. This research objective is directly related to firms' motivations for tying market transactions to public goods donations, and also consumers' inferences in response to these ties. One possibility is that firms attempt to use charity purely to increase profit, and if consumers correctly infer this motive, then consumers' incremental responses to charity links should reflect only their utility value from the charitable action. A second view suggests that charitable actions by firms act as credible signals of quality or trustworthiness, and positive consumer responses will incorporate *both* their own value for the public good and also their belief that the market transaction will be conducted favorably.

We explore these theories using a large sample of eBay listings, matched by seller, product, and start price. This sample comprises more than 22,000 "experiments" run by eBay sellers from January 2005 to March 2008, generating more than $4.2 million in product sales. This data set allows us to control for unobserved heterogeneity across sellers and products in a real market environment. It also allows us to examine difference in the impact of charity tie-ins across sellers with different attributes, a question which

[30] In addition to the results described here and reported in Table 9, we investigated whether there is an annual change to the GW effect during September through November more generally, which might explain the results in columns (1) and (2). We found that this "Katrina placebo" has no impact on GW sale probabilities or maximum bids. We also investigated the impact of Katrina-era GW listings by donation level, as in Table 5, and found that changes to charity salience have an impact across donation levels.

would be nearly impossible to replicate in a field experiment. A final advantage of our approach is that it allows us to examine the role of bundling private and public goods in a setting in which marketing efforts of firms are not conflated with choices to commit to charitable donations. While these marketing efforts may be important for firms to get the full returns from charitable commitments, they may obfuscate the relative importance of the charitable donation itself.

Our analysis has three main findings. First, consistent with Elfenbein and McManus (2010) we find that charity links have positive but limited impacts on consumer demand: products that trigger charitable donations have a higher likelihood of sale, attract more bids, and sell for higher prices than those that do not—even when controlling for heterogeneity in sellers and start prices. Moreover, the charity impact is stronger the larger the fraction donated to charity. Second, we find that low-feedback sellers benefit much more than high-feedback sellers when pledging charitable donations. Together with the fact that the overall direct returns are negative—even from 10% donations and even among low-feedback sellers—this result supports the signaling view of corporate philanthropy proposed by Fisman, Heal, and Nair (2006): other-regarding, altruistic sellers may credibly signal their trustworthiness by committing to make a donation to charity. In the presence of little information about the reliability of a seller, charity commitments play a significant role in establishing trust. Once the seller has established a history of reliability, the relative value of this signal is diminished. Finally, we show that the value consumers place on charity may be affected by shocks that increase the salience of charitable giving. Following Hurricane Katrina, the impact of charitable commitments on

the sale probability and price nearly doubled. These effects are observed for high and low feedback sellers alike, indicating that while quality signaling may be an important function of corporate philanthropy, in certain situations the commercial impact of charity tie-ins may be driven by the utility benefits consumers receive from contributing to public goods.

Overall the patterns we observe in the data suggest that consumer responses to charity tie-ins are driven both by opportunities for firms or managers with other-regarding preferences to signal their type and also – at least in certain situations – from the increment to consumers' utility that comes directly from purchasing the private-public goods bundle. Our results suggest that a full model of consumer choice might nest these considerations. Outside options, such as the ability to contribute directly to the public good of one's choice, may place strict limits on the ability of firms to directly appropriate the utility value of the bundle and effectively eliminate any arbitrage opportunities to raise profits from charity links (Elfenbein and McManus, 2010). These limits, in turn, create a separating condition that enables consumers to rationally infer that charity tie-ins are much more likely to be pursued by other-regarding firms or managers, and hence may serve as a signal of quality, as proposed by Fisman et al. (2006).

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 a reasonable one, because eBay does not record or reveal a seller's charitable donations for the use of potential customers. Although it is certainly possible to construct at least a recent history of giving for a particular seller, in the eBay context this is relatively time

consuming. However, to the extent that potential bidders do investigate sellers and draw quality inferences from charitable donations, our estimates for signaling will be under-estimated. A second limitation of this paper 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, while our paper provides suggestive evidence that consumers' perceptions of sellers' quality may be a driving force behind the impact of charitable commitments, we cannot conclusively distinguish the signaling model from other possibilities, such as affinity or reciprocity (Sugden, 1984; Fehr and Gächter, 2000; Charness, Rigotti, and Rustichini, 2007; Croson, 2007). While these alternative explanations are possible, they are difficult to reconcile with our findings that the benefits of seller charity accrue primarily to low feedback sellers. These alternative explanations would require a strong relationship between sellers' size and consumers' preferences.

The current paper represents a first step in understanding why firms perceive different levels of consumer benefit from charity tie-ins and green or ethical production. The evidence – albeit anecdotal – of the benefits of such practices is mixed. Vogel (2006), for example, examines the efforts of Starkist, Ciba, Ford, and British Petroleum to benefit from environmentally friendly production. He reports that executives at these firms conclude that customers are not willing to pay more for their "green" products. While our study does not address this issue directly, it does raise the possibility that consumers may make different inferences about firms' charitable actions based on the characteristics of the

firm. Large firms such as these – with well-established reputations and product lines – may not generate quality-signaling benefits from philanthropy or green practices. However, we are only at the very early stages of analyzing and understanding the inferences that consumers make from firms' contributions to public goods.

References

Akerlof, George. 1970. "The Market for Lemons: Quality Uncertainty and the Market Mechanism." *Quarterly Journal of Economics* 84 (3), 488-500.

Andreoni, James. 1989. "Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence." *Journal of Political Economy* 97(6), 1447-58.

Ariely, Dan and Itamar Simonson. 2003. "Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions." *Journal of Consumer Psychology* 13(1/2), 113-123.

Bagnoli, Mark, and Susan G. Watts. 2003. "Selling to Socially Responsible Consumers: Competition and the Private Provision of Public Goods." *Journal of Economics & Management Strategy* 12(3), 419-445.

Bajari, Patrick and Ali Hortacsu. 2004. "Empirical Insights from Internet Auctions: A Survey." *Journal of Economic Literature* 42(2), 457-486.

Baron, David P. 2007. "Corporate Social Responsibility and Social Entrepreneurship." *Journal of Economics & Management Strategy* 16(3), 683-717.

Baron, David P. 2009. "A positive theory of moral management, social pressure, and corporate social performance." *Journal of Economics & Management Strategy* 18(1), 7-43.

Cabral, Luis and Ali Hortascu. 2010. "The Dynamics of Seller Reputation: Theory and Evidence from eBay." Forthcoming, *Journal of Industrial Economics*.

Casadesus-Masanell, Ramon; Michael Crooke; Forest L. Reinhardt; and Vishal Vasisth. 2009. "Households' Willingness to Pay for 'Green' Goods: Evidence from Patagonia's Introduction of Organic Cotton Sportswear." *Journal of Economics & Management Strategy* 18(1), 2003-233.

Center on Philanthropy at the University of Indiana. 2006. *Giving USA 2005*, Giving USA Foundation.

Charness, Gary; Luca Rigotti; and Aldo Rustichini. 2007. "Individual Behavior and Group Membership." *American Economic Review* 97(4), 1340-1352.

Croson, Rachel T.A. 2007. "Theories of Commitment, Altruism and Reciprocity: Evidence from Linear Public Goods Games." *Economic Inquiry* 45(2), 199-216.

Elfenbein Daniel W. and Brian McManus. 2010. "A Greater Price for a Greater Good? Evidence that Consumers Pay More for Charity-Linked Products." Forthcoming, *American Economic Journal: Economic Policy*.

Fehr, Ernest and Simon Gächter. 2000. "Fairness and Retaliation: The Economics of Reciprocity," *Journal of Economic Perspectives*, 14(3), 159-81.

Fisman, Ray; Geoffrey Heal; and Vinay Nair. 2006. "A Model of Corporate Philanthropy." Working Paper, Columbia University and University of Pennsylvania.

Friedman, Milton. 1970. "The Social Responsibility of Business is to Increase its Profits." *The New York Times Magazine*. September 13 1970, 32-33, 122, 126.

Hauser Daniel, and John Wooders. 2006. "Reputation in Auctions: Theory, and Evidence from eBay." *Journal of Economics and Management Strategy* 15, 353-369.

Hiscox, Michael J. and Nicholas F.B. Smyth. 2008. "Is There Consumer Demand for Improved Labor Standards? Evidence from Field Experiments in Social Product Labeling." Harvard University Working Paper.

Jin, Ginger and Andrew Kato. 2006. "Price, Quality, and Reputation: Evidence from an Online Field Experiment." *RAND Journal of Economics* 37(4), 983-1005.

Lee, Young Han and Ulrike Malmendier. 2009. "The Bidders' Curse." University of California–Berkeley working paper.

Levitt, Steven. 2006. "White-Collar Crime Writ Small: A Case Study of Bagels, Donuts, and the Honor System." *American Economic Association Papers and Proceedings* 96(2), 290-294.

List, John A. 2006. "The Behavioralist Meets the Market: Measuring Social Preferences and Reputation Effects in Actual Transactions," *Journal of Political Economy* 114(1), 1-37.

Margolis, Joshua D. and James P. Walsh. 2003. "Misery Loves Companies: Rethinking Social Initiatives by Business." *Administrative Science Quarterly* 48, 268-305.

Margolis, Joshua D., Hillary A. Elfenbein, and James P. Walsh. 2007. "Does It Pay To Be Good? A Meta-Analysis and Redirection of Research on Corporate Social and Financial Performance." Harvard University Working Paper.

McKinsey and Company, "The state of corporate philanthropy," *The McKinsey Quarterly*, February 2008.

McManus, Brian and Richard Bennet. 2009. "The Demand for Products Linked to Public Goods: Evidence from an Online Field Experiment." University of North Carolina working paper.

Pivato, Sergio; Nicola Misani; and Antonio Tencati. 2008. "The Impact of Corporate Social Responsibility on Consumer Trust: The Case of Organic Food." *Business Ethics: A European Review* 17(1), 3-12.

Roberts, James W. 2009. "Can Warranties Substitute for Reputations?" Duke University working paper.

Sailer, Katharina. 2005. "Searching and Learning in Internet Auctions: The eBay Example." Ph.D. Dissertation, University of Munich.

Siegel, Donald S. and Donald F. Vitaliano. 2007. "An Empirical Analysis of the Strategic Use of Corporate Social Responsibility." *Journal of Economics & Management Strategy* 16(3), 773-792.

Sugden, Robert. 1984. "Reciprocity: The Supply of Public Goods through Voluntary Contributions." *Economic Journal* 94, 772-787.

Vogel, David. 2006. *The Market for Virtue: the Potential and Limits of Corporate Social Responsibility*. Washington, DC: Brookings Institution Press.

Appendix

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 (i) available: Giving Works (g) and non-Giving Works (n). Let π_i represent the probability of the item selling under format i during period (week) 0, when the item is first listed. Let p_i be the expected price of the item under format i 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 $p_i\boldsymbol{\delta_p^t}$, where δ_p is the weekly decline in the item's price. The per-period sales probability declines at rate δ_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 γ. The present discounted values of these two strategies are V_n and V_g, respectively. We do not allow the seller to switch between formats g and n or consider changing γ. The values V_i include eBay's listing fees, which are dependent on whether an item sells and its price conditional on selling. Let c 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. Under Giving Works, the seller is responsible to pay only (1–γ) of c 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 n may be written recursively as:

$$V_n = \pi_n[p_n - f_2(p_n - 25) - f_1 25] - c + (1 - \pi_n)\beta V_n, \quad \text{or}$$

$$V_n = \frac{\pi_n[p_n - f_2(p_n - 25) - f_1 25)] - c}{[1 - (1 - \pi_n)\beta]}.$$

When the final price is less than \$25 and p_n and π_n are constant, the PDV of selling an item under format n is:

$$V_n = \frac{\pi_n(p_n - f_1 p_n) - c}{[1 - (1 - \pi_n)\beta]}.$$

If p_n and π_n can change over time, then V_n 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 A2.

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 γ. For a final price above \$25, the PDV of selling an item under format g is:

$$V_g = \pi_g\left[(1-\gamma)\left(p_g - f_2(p_g - 25) - f_1(25)\right)\right] - (1-\gamma)c + (1 - \pi_g)\beta V_g \text{ or}$$

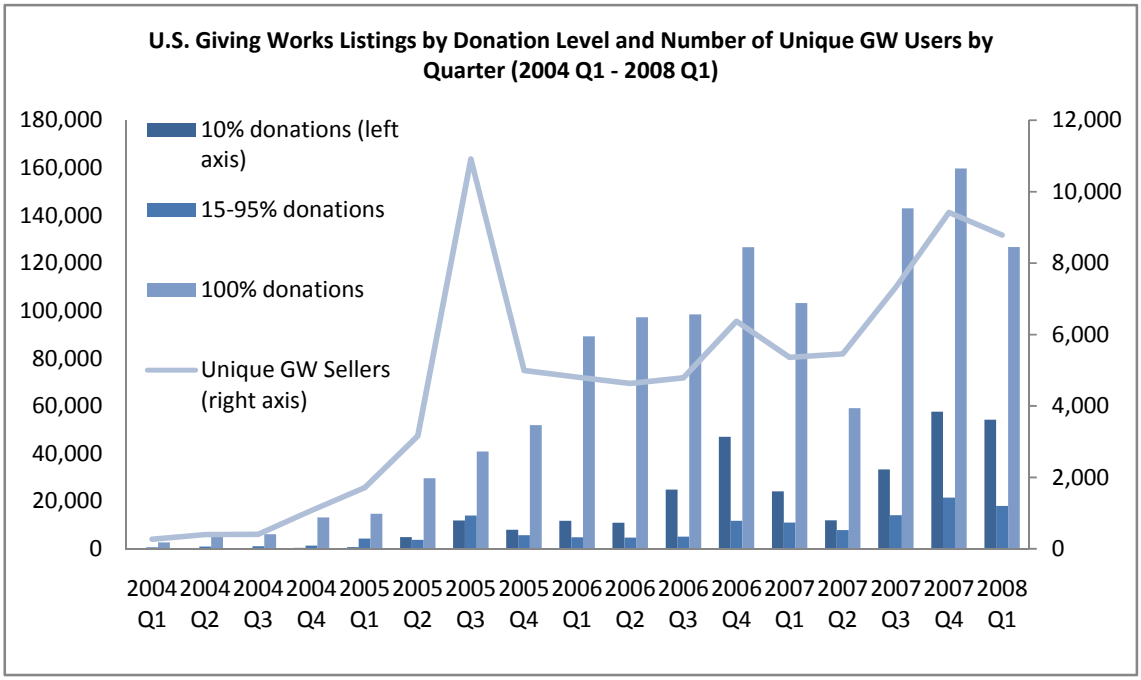
$$V_g = \frac{\pi_g\left[(1-\gamma)\left(p_g - f_2(p_g - 25) - f_1(25)\right)\right] - (1-\gamma)c}{[1 - (1 - \pi_g)\beta]}.$$

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

$$V_g = \frac{\pi_g[(1-\gamma)(1 - f_1)p_g] - (1-\gamma)c}{[1 - (1 - \pi_{cg})\beta]}.$$

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

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: SPSE data by seller
(N = 5,015)

	Mean	Median	Std. Dev	Min	Max
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 Meta categories *	1.90	1	1.81	1	25
N Level 2 categories *	2.64	2	4.18	1	83

Notes: Seller age is not available for all sellers; N = 4,723. The last two rows limit the sample to sellers with multiple matches; N = 2,021.

Table 2: SPSE data by match
(N=22,610)

	Mean	Median	Std. Dev	Min	Max
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
SKU present	0.014	0	0.117	0	1
Photo Count	0.049	0	0.216	0	1

Table 3: SPSE data by listing
(N = 162,505)

	Mean	Median	Std. Dev	Min	Max
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
SKU present	0.38	0	0.49	0	1
Photo Count	1.24	1	1.19	0	8
Non-Giving Works only (N = 75,618)					
Days between own start and nearest charity 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: N for sale price is 54,416. N for maximum bid is 63,689.

Table 4: Baseline effect of charity on sale probability and price

	(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	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 5: Baseline effect of donation percentage on sale probability and price

	(1)	(2)	(3)	(4)
Dependent Var.	Sold	# Bids	log(Price)	log(Maximum bid)
Donation=10%	0.0586***	0.106***	0.0215**	0.0217**
	(0.0118)	(0.0368)	(0.0103)	(0.00917)
10%<Donation<100%	0.102***	0.286***	0.0354*	0.0474**
	(0.0196)	(0.0553)	(0.0211)	(0.0186)
Donation=100%	0.137***	0.410***	0.0638***	0.0617**
	(0.0333)	(0.109)	(0.0238)	(0.0240)
Observations	104083	162766	54487	63841
R-squared	0.015	0.014	0.007	0.008

Notes: We include the same listing-specific control variables as listed in Table 4 but refrain from reporting coefficients due to space constraints. Standard errors, clustered on seller, are in parentheses. *** indicates significance at $p = 0.01$, ** for $p = 0.05$, and * for $p = 0.10$.

Table 6: Effect of feedback on "charity premium" in sale probability and price

	(1)	(2)	(3)	(4)
Dependent Var.	Sold	Sold	log(Maximum bid)	log(Maximum bid)
Charity	0.332***	0.386***	0.132***	0.171***
	(0.0574)	(0.0728)	(0.0328)	(0.0458)
log(Feedback)	-0.0324***		-0.0132***	
*Charity	(0.00758)		(0.00392)	
Feedback_Q2		-0.217***		-0.115**
*Charity		(0.0764)		(0.0510)
Feedback_Q3		-0.286***		-0.136***
*Charity		(0.0746)		(0.0490)
Feedback_Q4		-0.332***		-0.155***
*Charity		(0.0733)		(0.0467)
Observations	103650	104083	63294	63689
R-squared	0.019	0.021	0.009	0.010

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 7: Effect of feedback on "charity premium" in sale probability and price, by donation share.

	(1)	(2)	(3)	(4)
Dependent Var.	Sold	Sold	log(Maximum bid)	log(Maximum bid)
Donation=10%	0.166***	0.123***	0.0631***	0.0423
	(0.0288)	(0.0320)	(0.0238)	(0.0383)
10%<Donation<100%	0.308***	0.302***	0.111*	0.257***
	(0.0638)	(0.0907)	(0.0568)	(0.0701)
Donation=100%	0.553***	0.539***	0.266***	0.246***
	(0.103)	(0.0885)	(0.0718)	(0.0583)
Donation=10%	-0.0136***		-0.00547**	
*log(Feedback)	(0.00368)		(0.00279)	
10%<Donation<100%	-0.0297***		-0.0102	
*log(Feedback)	(0.00820)		(0.00756)	
Donation=100%	-0.0640***		-0.0322***	
*log(Feedback)	(0.0138)		(0.00953)	
Donation=10%		0.0250		0.00487
*Feedback_Q2		(0.0464)		(0.0453)
Donation=10%		-0.0515		-0.0114
*Feedback_Q3		(0.0405)		(0.0444)
Donation=10%		-0.0893***		-0.0309
*Feedback_Q4		(0.0340)		(0.0397)
10%<Donation<100%		-0.122		-0.278***
*Feedback_Q2		(0.102)		(0.101)
10%<Donation<100%		-0.220**		-0.223***
*Feedback_Q3		(0.0950)		(0.0757)
10%<Donation<100%		-0.224**		-0.213***
*Feedback_Q4		(0.0937)		(0.0749)
Donation=100%		-0.353***		-0.134**
*Feedback_Q2		(0.0970)		(0.0677)
Donation=100%		-0.403***		-0.204***
*Feedback_Q3		(0.0927)		(0.0678)
Donation=100%		-0.475***		-0.233***
*Feedback_Q4		(0.0915)		(0.0611)
Observations	103650	104083	63446	63841
R-squared	0.021	0.024	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 $p = 0.10$.

Table 8: Robustness of feedback results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Var.	Sold	log(Max. bid)	Sold	log(Max. bid)	Sold	log(Max. bid)	Sold	log(Max. bid)	Sold	log(Max. bid)
Charity	0.336***	0.142***	0.440***	0.157**	0.355***	0.157***	0.315***	0.151***	0.0296	-0.128
	(0.0568)	(0.0335)	(0.0868)	(0.0652)	(0.0679)	(0.0423)	(0.0584)	(0.0359)	(0.187)	(0.200)
log(Feedback)	-0.0343***	-0.0165***	-0.0292***	-0.0132***	-0.0312***	-0.0123***	-0.0330***	-0.0135***	-0.0306***	-0.0100***
*Charity	(0.00761)	(0.00434)	(0.00790)	(0.00413)	(0.00755)	(0.00369)	(0.00736)	(0.00402)	(0.00414)	(0.00320)
SKU	0.0218	0.0355*								
*Charity	(0.0265)	(0.0183)								
log(Seller age)			-0.0187	-0.00338						
*Charity			(0.0125)	(0.00911)						
Category Conc					-0.0473	-0.0439*				
*Charity					(0.0355)	(0.0255)				
log(Start Price)							0.00754	-0.00775*		
*Charity							(0.00700)	(0.00456)		
Charity X State Dummies?	No	No	No	No	No	No	No	No	Yes	Yes
Observations	103650	63446	101030	60802	103650	63446	103650	63446	101961	62436
R-squared	0.019	0.009	0.019	0.009	0.019	0.009	0.019	0.009	0.025	0.012

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 9: Impact of charity salience

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.	Sold	log(Max. bid)	Sold	log(Max. bid)	Sold	log(Max. bid)	Sold	log(Max. bid)
Charity	0.0931***	0.0361***	0.0540***	0.0156**			0.1019***	0.0442***
	(0.0160)	(0.0107)	(0.00897)	(0.00774)			(0.0157)	(0.0108)
Katrina era	0.0221	-0.00777	0.0255	-0.00318	0.0194	-0.00825		
	(0.0236)	(0.0250)	(0.0238)	(0.0264)	(0.0236)	(0.0255)		
Katrina era*Charity	0.0973***	0.0392	0.0994***	0.0387				
	(0.0279)	(0.0265)	(0.0271)	(0.0283)				
Katrina charity					0.0331**	0.0207*		
					(0.0134)	(0.0115)		
Non-Katrina charity					0.110***	0.0404***		
					(0.0186)	(0.0125)		
Katrina charity					0.161***	0.0568*		
*Katrina era					(0.0285)	(0.0297)		
Non-Katrina charity					0.0565	0.0271		
*Katrina era					(0.0402)	(0.0326)		
Holidays							0.0125	0.0217
							(0.0157)	(0.0188)
Holidays*Charity							-0.0108	-0.0319
							(0.0233)	(0.0201)
Sample	Full	Full	High feedback	High feedback	Full	Full	Full	Full
Observations	104083	63841	89054	52483	104083	63841	104083	63841
R-squared	0.015	0.008	0.008	0.008	0.016	0.008	0.013	0.008

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

Table A1: Fixed-effects regression of auction listing details on charity

Dependent variable	Constant	GW Indicator
Reserve price	148.185	-0.564
	(0.233)	(0.435)
Shipping fee	6.314	-0.093
	(0.054)	(0.102)
Scheduled length	6.176	0.094
	(0.045)	(0.085)
Bold listing	0.033	0.002
	(0.0008)	(0.002)
Featured	0.016	0.002
	(0.001)	(0.003)
Buy-it-now option	-0.337	-0.004
	(0.004)	(0.008)
SKU present	0.380	-0.002
	(0.0007)	(0.001)
Photo count	1.245	-0.006
	(0.0033)	(0.005)

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. Each reported estimate in the "Constant" column is significantly different from zero at $p < 0.001$. None of the reported estimates in the "Giving Works" column is significantly different from zero at $p < 0.10$.

Table A2: Estimates of present value of revenue net of listing costs and donations

	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.

Table A3: Giving Works impact on log(price) when donation is 10%

	(1)	(2)
Dependent Var.	log(price)	log(price)
Donation=10%	0.0215**	0.0351
	(0.0103)	(0.0280)
log(Feedback)		-0.00175
* Donation=10%		(0.00371)
Observations	54416	54177
R-squared	0.007	0.008

Notes: Column (1) represents an identical regression to Table 5, Column (3). Column (2) repeats the regression of Table 7, Column (1) using log(price) as the dependent variable. In both reported regressions above all coefficients except those of interest are suppressed. Standard errors, clustered by seller, are in parentheses. *** indicates significance at $p = 0.01$, ** for $p = 0.05$, and * for $p = 0.10$.