Market Punishment of Strategic Generosity: An Empirical Examination of NFT Charity Auctions

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Abstract

Cryptocurrencies and blockchain technology have had a disruptive influence on financial markets, including philanthropy. In recent years, crypto donations have grown to comprise a significant fraction of charitable donations worldwide. NFT charity auctions, which involve the sale of artistic works as non-fungible tokens with proceeds donated to a philanthropic cause, have been an important development in this space, with several platforms catering directly and specifically to the phenomenon. A unique aspect of NFT charity auctions is that donors may be perceived as altruistic, but they also may be perceived as motivated by financial incentives, due to the potential for rapid increases in the value of charity NFTs they may purchase, and thus the potential for 'donors' to reap financial gains. NFT charity auctions thus offer a unique opportunity to understand how social image may translate into quantifiable economic penalties for donors, in their subsequent NFT market activity. We explore this in the context of a large NFT charity auction that was undertaken in support of Ukraine, in its conflict with Russia. We investigate the impact of donating to charity through NFTs on future NFT sales performance using a difference-in-differences (DiD) model. We examine the consequences of charity NFT purchase and subsequent relisting, finding that donors who engage in such behavior experience a systematic penalty in terms of the prices they can command in the later sale of other NFTs in their portfolio. Specifically, we estimate that 'strategically generous' donors experience a statistically significant decrease of 4.78% in their NFT sale prices following their participation in the Ukraine charity auction. We demonstrate that these effects accrue, specifically, to donors who re-listed their Ukraine NFTs for sale shortly after purchase, and to those who are more socially embedded in the NFT community. Overall, our study underscores the importance of digital visibility and traceability that characterize crypto-philanthropy, and it offers valuable practical implications for stakeholders in this space.

Keywords: blockchain, NFT, crypto philanthropy, strategic generosity

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1. Introduction

Cryptocurrencies, and blockchain technology more generally, have had a disruptive influence on financial markets over the last 15 years. This disruption has even extended to philanthropy in recent years (Tan and Tan 2022), as crypto donations comprise an increasing fraction of charitable donations around the world. According to Fidelity's non-profit arm, Fidelity Charitable, nearly half of all cryptocurrency investors make charitable donations, and Fidelity itself has received $331 million in cryptocurrency donations in 2021 alone, nearly 10 times the volume received over the year prior. Further, many of the world's best known charitable organizations now accept cryptocurrency donations, including the American Red Cross, Khan Academy, Oxfam, UNICEF, and the YMCA.

Within the broader context of crypto philanthropy, charity auctions focused on artistic work, minted as non-fungible tokens, or NFTs (Kanellopoulos et al. 2021), have grown particularly prevalent of late.[4] Typically, works of art are commissioned or contributed by artists, which are then sold, and all or a portion of the proceeds are allocated toward a philanthropic organization or pursuit. A number of NFT charity auctions, organized by the likes of Bill Murray,[5] Sotheby's,[6] and Taco Bell,[7] have been massively successful in the last two years, and several platforms have even begun to emerge that cater directly to this phenomenon, offering venues for NFT sales that allocate all or a portion of proceeds toward philanthropic pursuits, e.g., DoinGud[8] DigitalArt4Climate.[9]

[4] https://cointelegraph.com/news/nft-philanthropy-demonstrates-new-ways-of-giving-back
[5] https://www.coindesk.com/business/2022/08/31/beer-with-bill-murray-nft-sells-for-185k-in-eth-at-charity-auction/
[6] https://cointelegraph.com/news/sotheby-s-metaverse-announces-latest-and-largest-nft-charity-auction
[7] https://charitydigital.org.uk/topics/topics/nfts-for-good-how-charities-can-fundraise-with-nfts-8899
[8] https://doingud.com/
[9] https://digitalart4climate.space/

A unique aspect of crypto philanthropy is that donors have the potential to benefit directly from what are, ostensibly, prosocial donations (Tan and Tan 2022). In the context of NFT charity auctions, this may occur because NFTs, and the underlying cryptocurrencies to which they are tied, have the potential to exhibit rapid increases in value, behind a highly volatile asset. By purchasing NFTs as part of a charity auction, buyers may thus stand to turn a quick profit from subsequent resale. This dynamic implies that, although donors may be motivated out of altruism, they could also be motivated primarily by financial incentives. Depending on the inferences that onlookers may make about donors' motivations, this dual possibility has clear implications for donors' social image.

Extensive research in economics and psychology has documented evidence that image concerns shape a variety of behaviors (Bursztyn & Jensen 2017), including numerous prosocial activities, such as volunteering (Carpenter and Myers 2010), blood donation (Lacetera and Macis 2010), and charitable contribution (Benabou and Tirole 2006; Kafashan et al. 2014; Simpson and Willer 2015). Work argues and shows that individuals are more likely to engage in prosocial behavior when their social image will benefit from doing so (Lacetera and Machis 2010). Conversely, work shows that individuals are less likely to engage in prosocial behavior when potential benefits are absent, or undermined by the publicly observable presence of possible extrinsic incentives, such as financial compensation (Benabou and Tirole 2006).

While a great deal of work studies the question of how social image concerns affect individuals tendency to engage in prosocial behavior, little work has examined the perspective and perception of onlookers (Berman and Silver 2022), examining whether and to what extent donors may experience economic penalties as a result of negative social image, deriving from the perception of strategic generosity. We address those questions here, in the context of a large NFT charity auction, employing data related to an auction undertaken in support of Ukraine, regarding its military conflict with Russia. We analyze a panel dataset that comprises 14 months, encompassing seven months before and after the NFT charity auction date of February 26, 2022. Specifically, we focus on NFT-related activities among a group of 2836 contributors who successfully made donations, as well as 2856 individuals who attempted but were unable to donate.

To obtain causal estimates, our identification strategy exploits random variation in donors' ability to obtain the NFTs that were sold at auction. The auction in question involved the sale of a limited number of NFT units. As the number of NFT sales approached capacity, many interested donors attempted to complete a purchase, yet failed, due to plausibly exogenous variation in transaction processing times on the blockchain. We examine the consequences of successful purchase and subsequent re-listing of charitable NFTs on donors' subsequent market outcomes. We find that these donors experience a systematic penalty in the prices they are able to command in the market. In particular, we estimate that users' who purchase the Ukraine NFT see significant declines in sale prices for other NFTs in their portfolio, to the tune of 4.78%. Further, we show that these effects accrue specifically to those donors who i) re-listed their Ukraine NFTs for sale, shortly after initial purchase, and ii) who are more socially exposed, as a result of greater social embeddedness in the NFT community, i.e., holding a greater number of friends and followers.

Our study contributes to the literature on social image and pro-social contribution, as well as the literature on crypto-philanthropy. Our work offers unique insights into the dynamics of social penalties and ostracism that arise in response to perceived strategic generosity. As recent work observes, field evidence for the role of social image in prosocial contributions is generally hard to come by, a fact that has resulted in a heavy focus upon laboratory experiments (Exley 2018). NFT charity auctions provide a research context that uniquely lends itself to the study of social image, in large part because all transactions, involved parties, and associated prices, are publicly observable, auditable, and traceable on the blockchain.

Our work bears several implications for theory and practice. With regard to practical implications, first, the findings suggest that donors to NFT charity auctions may face negative economic consequences in the form of lower prices for their NFTs in subsequent transactions. This finding could influence the behavior of potential donors and may have implications for the long-run success of NFT charity auctions. To the extent donors recognize and experience economic penalties, their participation may decline in the long-run. Further, our study highlights the importance of considering the role of social image concerns in charitable giving, not only from a donor's standpoint, but also from the perspective of third-party onlookers. While donors may be motivated by both altruistic and strategic considerations, and concerns about third-party perceptions may influence their choices about whether and how much to contribute, our work demonstrates that onlookers' true perceptions are also important to consider. To the extent onlooker perceptions may deviate from actors' predictions or expectations, donors may select out of donation on the basis of invalid concerns, or they may engage in donation inefficiently, to their own detriment.

With regard to theory, our study contributes to the broader literature on the role of social image concerns in prosocial behavior, particularly in the context of charitable giving and donation. The findings demonstrate the extent to which the negative social consequences that donors experience may also translate to negative economic consequences as well. Our work also contributes to the nascent literature on crypto-philanthropy. In short, we demonstrate the influence of an important feature of NFTs and blockchain, namely the public visibility and traceability of transactions, in this new context of charitable giving.

2. Literature Review

2.1. Image Concerns & Prosocial Behavior

Several empirical studies in economics have identified that social image concerns can have powerful effects on a range of behaviors, including prosocial behavior such as charitable donations. The reviewed studies provide insights into the underlying mechanisms of social image concerns and extrinsic incentives, and how each may affect prosocial behavior. Lacetera and Macis (2010), employing longitudinal data on blood donation, examine how donors respond to symbolic prizes for reaching donation quotas. They observe that these symbolic prizes, a form of positive social recognition, have a positive influence on donation activity, particularly when announced publicly.

Monetary compensation may have the opposite influence, however, as it may induce a perception of greed. Reflecting this, Carpenter and Myers (2010) found that altruism and social image concerns were positively correlated with the decision to volunteer as a firefighter. Further, those authors observed that monetary incentives can also drive willingness to volunteer, but that these motivational benefits of payment decline when knowledge of the monetary incentives is made public, suggesting that extrinsic incentives crowd out social image benefits as a motivation for prosocial behavior. However, it appears that extrinsic incentives in the form of status and recognition do not have the same effect.

Benabou and Tirole (2006) develop a theory of prosocial behavior that formalizes the rationale for these effects, combining heterogeneity in individual altruism or greed with concerns for social reputation or self-respect. Those authors identified that extrinsic incentives, in the form of rewards or punishments, whether material or image-related, can induce a partial or net crowding out of prosocial behavior.

More recently, the literature in this space has begun to shift focus from the role of image and incentives as motives for prosocial contributions, toward the perception and interpretation of third-party onlookers. Kafashan et al. (2014) examine the interactions between social status and prosocial behavior and show that causation may flow in both directions. Berman et al. (2015) study the braggart's dilemma and consider how bragging about prosocial behaviors may raise or lower an individual in the eyes of others, in terms of their perceived generosity. Those authors find that such bragging has a positive effect when prosocial behavior is unknown to onlookers, yet that it signals a selfish motive when the prosocial behavior is already known.

Bliege Bird et al. (2018) highlight how highly visible prosocial displays may be effective for attracting new partners, e.g., in trade, whereas more subtle signals may be crucial for ensuring trust and commitment on the part of long-term partners. In each case, the authors demonstrate that a positive social image, achieved via observable prosocial acts, has important impacts on actors' reputations and their ability to obtain future transaction partners.

Most recently, Berman and Silver (2022) review recent literature in this space and identify a variety of factors that influence whether and when observers may praise or denigrate a prosocial actor for doing a good deed. These authors note, for example, that individuals are more likely to look skeptically on a prosocial actor when they view themselves as being somehow in competition with the individual, or if they hold the concern that the other actors' behaviors may somehow be compared with the onlooker's own behaviors, making the onlooker seem bad in comparison. Berman and Silver (ibid) also dedicate a great deal of discussion to the issue of self-promotion. They note that self-promotion may be viewed negatively, and as evidence of self-interest, but that self-promotion may also lead to more positive attributions, when the information conveyed in the self-promotion is novel and informative, causing the recipient to update their prior beliefs about the prosocial actor. Nonetheless, subtle signals of self-promotion can yield benefits, as smaller scale efforts at self-promotion may be viewed as less brash and status-seeking. Finally, these authors note that self-promotion is also normative; to the extent many people engage in such behavior, it may be perceived as more socially acceptable.

The above points raise interesting questions for social dynamics and economic premiums or penalties may play out in an NFT market around a charity auction. While a perception of strategic generosity may ensue, when individuals attempt to sell their NFTs for financial gain, and that this may, in turn, affect individuals' ability to attract subsequent transaction partners in the market (Bliege Bird et al. 2018), it is also possible that individuals may ignore such information. For example, if NFT re-sale is perceived as common or expected, i.e., the norm (Berman and Silver 2022), onlookers may infer little from the behavior.

2.2. Crypto-philanthropy & NFT Charity Auctions

Crypto-currencies have disrupted financial markets broadly (Catalini et al. 2022), and the market for philanthropy is no exception (Tan and Tan 2021). The proportion of charitable donations now made in cryptocurrency has been on the rise, globally, exhibiting a ten-fold increase between 2020 and 2021 according to Fidelity Charitable,[10] and recent estimates indicate that 10% of the US adult population now holds some form of cryptocurrency.[11]

NFTs, or Non-Fungible Tokens, are digital assets stored on a blockchain, a decentralized and distributed digital ledger technology. Unlike traditional cryptocurrencies, NFTs are unique (hence the term 'non-fungible'), with each NFT tied to a particular asset, whether physical, e.g., real estate, or digital, e.g., artistic images, videos, or audio clips. The ownership of an NFT is

[10] https://www.fidelitycharitable.org/insights/cryptocurrency-and-philanthropy.html
[11] https://www.insiderintelligence.com/insights/us-adults-cryptocurrency-ownership-stats/

recorded on the blockchain, which provides proof of ownership and ensures that the asset is unique and cannot be duplicated or altered. This makes NFTs attractive for creators of digital art, collectibles, and other unique digital items who want to protect the authenticity and value of their creations. NFTs are bought and sold on digital marketplaces, e.g., OpenSea, with the value of each NFT being determined by supply and demand. As with any market, the value of NFTs can fluctuate depending on a variety of factors such as popularity, rarity, and perceived value. While NFTs have been around for several years, they have gained significant attention and popularity of late, as a result of high-profile sales of NFT-based digital art, reaching millions of dollars.

A small literature in IS has begun to examine aspects of NFT markets, as well as the consequences of introduction for more established markets. For example, recent work by Kanellopoulos et al. (2021) examines the effect of digital NFT collectibles on the price and demand for physical counterparts, in the context of basketball trading cards. Further, Hallaburda et al (2021) conceptually discuss the nature of NFTs, the novel functionalities they afford, and new types of markets they may enable, generally. However, by far, NFTs greatest area of adoption to date has been in the realm of art (Kugler 2021). Many NFT markets have begun to engage in art auctions, and charitable auctions in particular, with several dedicated platforms emerging for specifically this purpose. A limited supply of NFT artwork is first contributed (minted) by artists, and then sold, with all or a portion of the proceeds being allocated toward a philanthropic organization.

Philanthropy involving NFTs provides an interesting context for the study of social image. While there is a small prior literature on charity auctions (Carpenter et al. 2008; 2010; Elfbein and McManus 2010; Leszczyc and Rothkopf 2010), addressing why people participate, the efficacy of different auction formats, and showing that individuals are willing to pay more for the same item when their payment is linked to charity, the prior literature has focused little on the role of financial returns to donors, or on the perception of said by third parties. This is likely because donors' financial benefits, to the extent they do exist, are only likely to manifest over the long term, and are generally not visible to onlookers. NFT charity auctions are different, of course, because there is the significant potential for short-run financial gains, due to the highly speculative, volatile nature of NFT value (Zaucha and Agur 2022), and because the role of the blockchain makes resale and subsequent transaction highly visible to others in the market. In turn, this creates the potential for social image to significantly influence an ostensibly prosocial donor's ability to conduct future transactions in the marketplace.

3. Research Context and Data

Our study utilizes a dataset of NFT transactions that are linked to individuals (wallets) who attempted to purchase NFTs of a charity auction aimed at supporting Ukraine in its conflict with Russia. To collect the data, we sourced information from two APIs - the Etherscan API, which provided auction bid information, and the Rarible API, which provided NFT-related activities of users. We constructed a panel dataset spanning 14 months, from August 2021 to September 2022, which includes seven months before and after the treatment on February 26, 2022. Our sample includes 2836 contributors who successfully donated and 2856 individuals who were unable to donate. We provide descriptive statistics for our sample in Table 1.

Table 1. Descriptive Statistics

Variable	Definition	Mean	SD	Min	Max
Treated	A dummy variable; =1 since the month when the user successfully purchases a charitable NFT and onward, and equals zero otherwise	0.263	0.440	0.000	1.000
LnNumSales	Number of NFTs the user sold in that month (logged)	0.467	0.998	0.000	9.021
LnSaleAmount	The total sale price of NFTs sold by the user in that month (logged)	0.227	0.607	0.000	6.601
LnNumListings	Number of NFTs the user listed in that month (logged)	0.463	1.076	0.000	10.174
ListCharitableNFT	Whether the user lists the charitable NFT for sales	0.275	0.447	0.000	1.000

Note: We add the value of 1 to all continuous variables prior to performing the log transformation.

4. Research Design and Identification

4.1. Research Design

We leverage a panel dataset where the treatment is an NFT fundraising campaign on a popular NFT marketplace. In particular, we use a difference-in-differences (DiD) model (Angrist and Pischke 2008, Burtch et al. 2018) to estimate the changes in behaviors for users who successfully contributes to the campaign wherein the counterfactual are those users with similar intentions to contribute but failed to do so due to a sudden stock out within 5 minutes. Ideally, to establish the causal effect of charitable donations made through the purchase of charitable NFTs, a random assignment of successful bids would be preferred. However, this is infeasible in the NFT marketplace. As an alternative, we employ a quasi-experimental design that leverages the variation in processing time among similar bids submitted by comparable users. Given that all charitable NFTs were sold at the same price within 5 minutes, even small variations in processing time can greatly affect the treatment assignment. Specifically, we divide users into two groups: the treatment group, composed of users who successfully purchased the charitable NFTs, and the control group, composed of users who attempted to purchase the NFTs but were unsuccessful due to stock-out. By comparing these two groups, we aim to evaluate the impact of charitable NFTs on users' future sale performance. In the following section, we will elaborate on our matching strategy.

4.2. Matching

To ensure comparability between the treatment and control groups, we use the coarsened exact matching (CEM) method (Blackwell et al. 2009) to match both groups. The CEM method allows us to match both groups based on the minute at which they submit their bids for the charitable NFT, the level of the gas fee[12] (whether it is higher than, equal to, or lower than the mode gas fee), and the log average number of NFTs that they minted, purchased, sold, listed, and transferred in the months prior to the NFT charity auction. As Table 2 shows, all of the covariates exhibit high comparability between the treatment and control groups after the matching process.

Table 2. Balance Check for the CEM Sample

	Mean			t-test		V(T)/V(C)
Variable	Treated	Control	%bias	t	p>t	
MinuteId	3.404	3.404	0.000	0.000	1.000	1.000
LowGas	0.209	0.209	0.000	0.000	1.000	.
ModeGas	0.355	0.355	0.000	0.000	1.000	.
HighGas	0.436	0.436	0.000	0.000	1.000	.
LnAvgMints	0.859	0.846	1.400	0.290	0.772	1.000
LnAvgPurchases	0.167	0.198	-5.700	-1.220	0.223	0.990
LnAvgSales	0.503	0.492	1.300	0.270	0.788	1.030
LnAvgListing	0.551	0.553	-0.200	-0.040	0.967	0.990
LnAvgTransfers	0.483	0.498	-2.100	-0.460	0.644	1.010

4.3. Empirical Model

The main DID model used for the empirical analysis is

[12] In Ethereum, the time it takes to complete the transaction can be anywhere between 15 seconds and 5 minutes and depends on various factors (e.g., the gas fee, the congestion of the Ethereum network) (see more on https://legacy.ethgasstation.info/blog/ethereum-transaction-how-long/). As such, users have the option to increase the likelihood of a successful purchase by submitting their bids earlier (if possible) and increasing the gas fee. Usually, the Ethereum-based platform will provide the recommended gas fee, but users can specify a gas fee higher or lower than the recommended one depending on their willingness to pay for the charitable NFT.

$$Y_{it} = \beta_0 + \beta_1 Treated_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (1)$$

The dependent variable, Y_{it}, represents the NFT sales performance of user i in month t, including both the number of NFTs sold and the total sales price. The independent variable of interest, $Treated_{it}$, is a binary variable that equals one from the month when user i successfully purchases a charitable NFT and onward, and equals zero otherwise. γ_i denotes the user-specific fixed effects and δ_t represents the month-specific fixed effects. ε_{it} is an error term that is clustered at the user level to account for the potential correlation of errors over time for a given user.

5. Results

5.1. Main Results: Average Treatment Effect (ATE)

As Table 3 shows, the treatment effect on the number of NFTs users sold is only marginally significant or not significant. By comparison, the treatment significantly reduces users' NFT total sell prices by 4.78%. Besides, we find that, after controlling for the lagged terms of the number of NFTs users sold and listed, there is still a significant negative treatment effect on the sell prices. The findings suggest that the charitable NFT purchase, unexpectedly, leads to a negative impact on users' NFT sale performance by lowering the price of NFT sold.

Table 3. Average Treatment Effect

Dependent variable:	LnNumSales	LnSaleAmount	LnNumSales	LnSaleAmount
Treated	-0.070*	-0.049**	-0.035	-0.034**
	(0.039)	(0.019)	(0.025)	(0.015)
LagLnNumSales			0.325***	0.127***
			(0.020)	(0.013)
LagLnNumListings			0.123***	0.108***
			(0.015)	(0.011)
Fixed Effects on Users	Yes	Yes	Yes	Yes
Fixed Effects on Months	Yes	Yes	Yes	Yes
Observations	26,026	26,026	24,167	24,167
Num of Users	1,859	1,859	1,859	1,859
R-squared	0.491	0.496	0.595	0.580

Note: Robust standard errors clustered at the user level; * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

5.2. Heterogeneous Treatment Effect (HTE) by Intention to Resale

To gain a deeper understanding of why the charitable NFT purchase has a negative impact on users' NFT sales, we further examine the treatment effect based on whether the treated users intended to resell the charitable NFT. According to recent literature, when a firm's support for justice is perceived as performative and inauthentic, this may lead to a negative effect on its product sales (Wang et al. 2022). This phenomenon may be applicable to users' purchases of charitable NFTs if they are perceived as lacking authenticity and being strategic. To examine this possibility, we incorporate a moderator variable, $ListCharitableNFT_i$, which indicates whether the user lists the charitable NFT for sale in his/her portfolio within the first three days.[13]

Interestingly, as shown in Table 4, we find that only those treated users who intended to resell the charitable NFT experienced a negative treatment effect. This result supports the explanation that the market punishment of strategic generosity is at play and suggests that listing a charitable NFT for resale has a detrimental effect on the sales of other NFTs in the user's portfolio.

Table 4. HTE by Intention to Resale

Dependent variable:	LnNumSales	LnSaleAmount	LnNumSales	LnSaleAmount
Treated	-0.058	-0.013	0.033	0.035**
	(0.043)	(0.020)	(0.028)	(0.015)
Treated × ListCharitableNFT	-0.024	-0.069***	-0.130***	-0.132***
	(0.048)	(0.023)	(0.031)	(0.019)
LagLnNumSales			0.325***	0.128***
			(0.020)	(0.013)
LagLnNumListings			0.124***	0.108***
			(0.015)	(0.011)
Fixed Effects on Users	Yes	Yes	Yes	Yes
Fixed Effects on Months	Yes	Yes	Yes	Yes
Observations	26,026	26,026	24,167	24,167
Num of Users	1,859	1,859	1,859	1,859
R-squared	0.491	0.497	0.595	0.581

Note: Robust standard errors clustered at the user level; * p<0.1, ** p<0.05, *** p<0.01.

[13] For users in the treatment group who list their charitable NFTs for sale, 93.2% of them list the NFT within the first three days after their original purchase. This result is highly consistent when using the alternative measure of whether the user has ever listed the charitable NFT for sale within the observation window.

Furthermore, to bolster the explanation of the market publishment of strategic generosity, we construct two time-varying treatment status indicators: 1) $TreatedNoCharitableListing$, a binary variable that equals 1 if the user has purchased the charitable NFT without listing it for sale, and 2) $TreatedCharitableListing$, a binary variable that equals 1 if the user has purchased the charitable NFT and listed it for resale. If the market punishment of strategic generosity is present, we expect that the negative effect on users' NFT sales would be more pronounced for those who have both purchased and listed the charitable NFT. Our results, reported in Table 5, support this expectation. The coefficient of $TreatedCharitableListing$ is significantly negative with respect to the total sale price of other NFTs in the user's portfolio, adding evidence to the market punishment of strategic generosity.

Table 5. HTE by Treatment Status

Dependent variable:	LnNumSales	LnSaleAmount	LnNumSales	LnSaleAmount
TreatedNoCharitableListing	-0.079*	-0.022	0.025	0.033**
	(0.043)	(0.019)	(0.028)	(0.015)
TreatedCharitableListing	-0.063	-0.071***	-0.084***	-0.089***
	(0.048)	(0.024)	(0.031)	(0.019)
LagLnNumSales			0.326***	0.128***
			(0.020)	(0.013)
LagLnNumListings			0.124***	0.108***
			(0.015)	(0.011)
Fixed Effects on Users	Yes	Yes	Yes	Yes
Fixed Effects on Months	Yes	Yes	Yes	Yes
Observations	26,026	26,026	24,167	24,167
Num of Users	1,859	1,859	1,859	1,859
R-squared	0.491	0.496	0.595	0.581

Note: Robust standard errors clustered at the user level; * p<0.1, ** p<0.05, *** p<0.01.

With the aim of explaining the detrimental impact of the intention to resell charitable NFTs in light of the market punishment for strategic generosity, we investigate the variation in this effect by the user's level of public exposure within the NFT community. Using whether the user has any followers on the NFT marketplace prior to the treatment as a proxy for public exposure, we evaluate the impact of the previously discussed two treatment statuses on total sale price by levels of public exposure. The findings reported in Table 6 demonstrate that the negative effect on total sale price is more pronounced for users who have followers, as opposed to those who do not. This provides suggestive evidence for our explanation that the negative "bandwagon effect" will be more pronounced for users with higher levels of public exposure in the NFT community.

Table 6. HTE by Treatment Status and Public Exposure

Dependent variable:	LnSaleAmount	LnSaleAmount
TreatedNoCharitableListing	-0.013	0.040***
	(0.018)	(0.014)
TreatedCharitableListing	-0.029	-0.052***
	(0.023)	(0.018)
TreatedNoCharitableListing × Follower_Dum	-0.399	-0.320*
	(0.246)	(0.185)
TreatedCharitableListing × Follower_Dum	-0.715***	-0.631***
	(0.136)	(0.108)
LagLnNumSales		0.121***
		(0.013)
LagLnNumListings		0.110***
		(0.011)
Fixed Effects on Users	Yes	Yes
Fixed Effects on Months	Yes	Yes
Observations	26,026	24,167
Num of Users	1,859	1,859
R-squared	0.503	0.585

Note: Robust standard errors clustered at the user level; * p<0.1, ** p<0.05, *** p<0.01.

6. Robustness Checks

6.1. Parallel Trend Test

To assess the parallel trend assumption, we include multiple leads and lags in the DID model to check for any pre-treatment trend (Angrist and Pischke 2008; Burtch et al. 2018). As Figure 1 and Table 7 show, there is no statistically significant difference in the total sell prices of NFTs for both the treatment and control groups prior to the treatment period, thereby supporting the parallel trend assumption. Furthermore, even after controlling for the number of NFTs listed or sold by users in the previous month, the negative impact on total sell prices remains robust and persistent.

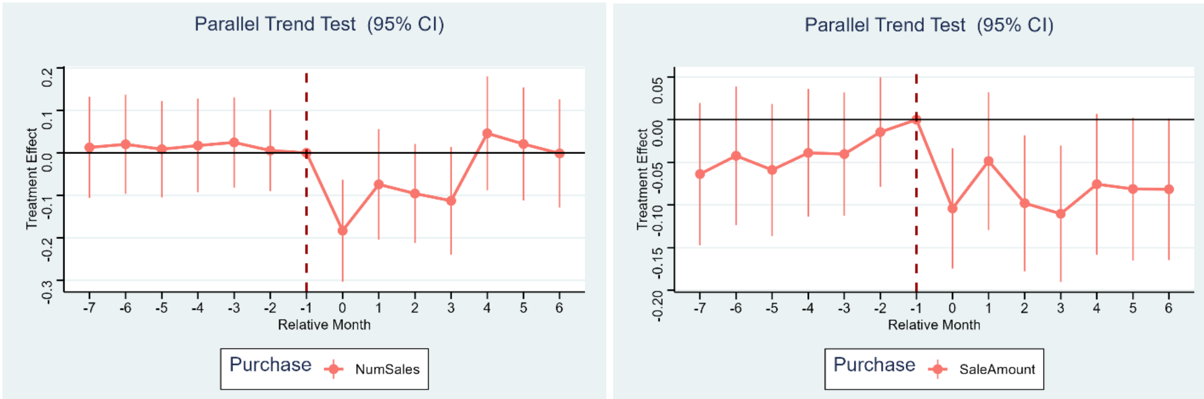

Figure 1. Coefficients of Leads and Lags Estimates

Notes: The dash vertical line denotes the month right before the treatment time. Error bars represent the 95% confidence intervals using the standard errors clustered by users.

Table 7. Parallel Trend Test

Dependent variable:	LnNumSales	LnSaleAmount	LnNumSales	LnSaleAmount
relative_month -7	0.013	-0.064		
	(0.061)	(0.043)		
relative_month -6	0.020	-0.042	0.014	-0.047
	(0.060)	(0.041)	(0.052)	(0.036)
relative_month -5	0.009	-0.059	0.003	-0.062*
	(0.058)	(0.040)	(0.050)	(0.034)
relative_month -4	0.017	-0.039	0.014	-0.041
	(0.056)	(0.038)	(0.051)	(0.033)
relative_month -3	0.025	-0.040	0.014	-0.048
	(0.054)	(0.037)	(0.052)	(0.034)
relative_month -2	0.005	-0.015	-0.005	-0.021
	(0.049)	(0.033)	(0.054)	(0.035)
relative_month -1		Baseline		
relative_month 0	-0.183***	-0.104***	-0.181**	-0.103**
	(0.061)	(0.036)	(0.071)	(0.041)
relative_month 1	-0.074	-0.049	0.017	0.002
	(0.067)	(0.041)	(0.060)	(0.039)
relative_month 2	-0.096	-0.098**	-0.059	-0.078**
	(0.060)	(0.041)	(0.056)	(0.039)
relative_month 3	-0.113*	-0.110***	-0.070	-0.089**
	(0.065)	(0.041)	(0.058)	(0.036)
relative_month 4	0.046	-0.076*	0.099*	-0.048
	(0.068)	(0.042)	(0.059)	(0.039)
relative_month 5	0.021	-0.081*	0.004	-0.089**
	(0.068)	(0.043)	(0.058)	(0.037)
relative_month 6	-0.001	-0.082*	-0.008	-0.085**
	(0.065)	(0.042)	(0.054)	(0.036)
LagLnNumSales			0.325***	0.127***

			(0.020)	(0.013)
LagLnNumListings			0.123***	0.108***
			(0.015)	(0.011)
Fixed Effects on Users	Yes	Yes	Yes	Yes
Fixed Effects on Months	Yes	Yes	Yes	Yes
Observations	26,026	26,026	24,167	24,167
Num of Users	1,859	1,859	1,859	1,859
R-squared	0.492	0.496	0.596	0.580

Note: Robust standard errors clustered at the user level; * *p*<0.1, ** *p*<0.05, *** *p*<0.01.

6.2. Alternative Matching Methods

To enhance the credibility of our results, we conduct robustness checks by utilizing several alternative matching and weighting methods, such as Propensity Score Matching (PSM) (Rosenbaum and Rubin 1983) and Covariate Balancing Propensity Score (CBPS) (Imai and Ratkovic 2014). The balance checks for these two methods are shown in Appendix A, suggesting that the treatment and control groups are highly comparable. The findings based on the PSM and CBPS samples, presented in Table 8, indicate that all results are remarkably consistent, providing further evidence for the robustness of our conclusions.

Table 8. ATE Based on Alternative Matching Methods

Sample	PSM		CBPS	
Dependent variable:	LnNumSales	LnSaleAmount	LnNumSales	LnSaleAmount
Treated	-0.159***	-0.128***	-0.143***	-0.124***
	(0.040)	(0.026)	(0.034)	(0.022)
Fixed Effects on Users	Yes	Yes	Yes	Yes
Fixed Effects on Months	Yes	Yes	Yes	Yes
Observations	66,626	66,626	79,688	79,688
Num of Users	4,759	4,759	5,692	5,692
R-squared	0.610	0.622	0.609	0.622

Note: Robust standard errors clustered at the user level. Results are highly consistent if we control for the number of NFTs the user listed and sold in the previous month. * *p*<0.1, ** *p*<0.05, *** *p*<0.01.

6.3. Alternative Sample

To further strengthen the validity of our findings, we perform robustness checks by limiting the sample to users whose bids were submitted within three minutes before and after those charitable NFTs were sold out. After implementing CEM on the same set of covariates discussed in Section

4.2, we observe that the newly matched users in both groups are highly comparable. Furthermore, our results (reported in Appendix B) show that the treatment significantly reduces the total sell prices of other NFTs in the users' portfolios.

6.4. Instrumental Variable

Furthermore, in addition to using the DID estimation method, we also employ another identification strategy, that is, instrumental variable (IV). In our matched sample, users in both the treatment and control groups submitted their bids within the same minute and set the gas fee at the same level. However, the small differences in the processing time of these similar bids, which are beyond the users' control, may play a crucial role in determining whether their bids were confirmed before the charitable NFTs sold out. Thus, we use the log-transformed processing time as an instrument for the treatment group dummy and use its interaction with the *After* dummy (which is set to 1 after the NFT charity auction) as an instrument for the *Treated* dummy (Wooldridge 2010, *p.*154) to estimate the impact of successfully purchasing a charitable NFT on the sale prices of other NFTs in the users' portfolios.

In the first stage of our IV analysis, we find strong evidence of the instrument's validity. The interaction between the log-transformed processing time and the *After* dummy, used as the instrument, is significantly negatively correlated with the *Treated* dummy (coefficient = -0.324, *p*-value = 0.000). Furthermore, both the Cragg-Donald Wald F statistic and the Kleibergen-Paap rk Wald F statistic exceed the critical values of the Stock-Yogo weak instrument test, providing additional evidence against the presence of a weak instrument problem. The results of the second stage, reported in Table 9, consistently reveal that the treatment leads to a statistically significant negative impact on NFT total sell prices in the marketplace.

Table 9. IV Results

Sample	CEM (5 mins)		CEM (3 mins)	
Dependent variable:	LnNumSales	LnSaleAmount	LnNumSales	LnSaleAmount
Treated	-0.133***	-0.084***	-0.101*	-0.074***
	(0.047)	(0.024)	(0.053)	(0.026)
Fixed Effects on Users	Yes	Yes	Yes	Yes
Fixed Effects on Months	Yes	Yes	Yes	Yes
Observations	25,452	25,452	17,066	17,066
Num of Users	1,818	1,818	1,219	1,219
R-squared	0.147	0.130	0.128	0.108

Note: The "CEM (5 mins)" sample refers to the matched sample introduced in Section 4.2. The "CEM (3 mins)" sample refers to the matched sample introduced in Section 6.3 after we limit the sample to users whose bids were submitted within three minutes before and after the charitable NFTs were sold out. Robust standard errors clustered at the user level; * p<0.1, ** p<0.05, *** p<0.01.

7. Conclusion

This paper delves into the emerging trend of crypto donations and NFT charity auctions, which have become a significant source of charitable donations worldwide. As the value of charitable NFTs purchased by donors can rise rapidly, some donors may be viewed as genuinely altruistic, while others may be perceived as motivated by the potential for quick financial gains. Our study examines how a donor's social image may affect their subsequent NFT market activity and lead to economic penalties. Specifically, we analyze a large NFT charity auction held in support of Ukraine during its conflict with Russia.

To investigate the impact of charitable NFT purchases on donor behavior and market outcomes, we divided donors into two groups: the treatment group of successful NFT purchasers and a control group of individuals who attempted yet failed to purchase NFTs due to blockchain processing times and stock out. We analyzed the consequences of successful purchasers and subsequent re-listing of charitable NFTs on donors' market outcomes. Our results indicate that purchasers of the Ukraine NFTs experienced a significant decline of 4.78% in the sale prices of other NFTs in their portfolio. This effect is more pronounced for donors who re-listed their Ukraine

NFTs for sale soon after purchase and had a higher level of social embeddedness in the NFT community, as evidenced by their larger number of friends and followers.

Our research has several implications for both theory and practice. First, our findings suggest that donors to NFT charity auctions may face economic penalties in the form of lower prices for their NFTs in subsequent transactions. This could potentially discourage future donors and may impact the long-term success of NFT charity auctions. Second, our study highlights the importance of social image concerns in charitable giving, not only from the donor's perspective, but also from the viewpoint of third-party onlookers. While donors may be motivated by altruistic and strategic considerations, concerns about how they are perceived by others can also influence their decisions about whether and how much to contribute. This may lead to donors making inefficient or suboptimal donations, which can ultimately harm the charity campaign.

Our study contributes to the literature on social image concerns and prosocial behavior, specifically in the context of charitable giving and donations. We provide unique insights into the mechanisms of social penalties and ostracism that arise when strategic generosity is perceived. Our findings illustrate how the negative social consequences experienced by donors can also lead to negative economic outcomes. Additionally, our study adds to the emerging field of crypto-philanthropy, highlighting the influence of the public visibility and traceability of transactions, a key feature of NFTs and blockchain, on charitable giving. In sum, our research demonstrates the importance of social image concerns on charitable donations, and how they may affect both donors and the long-term success of NFT charity auctions.

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Appendix A.

Table A1. Balance Check for PSM

	Mean			t-test		V(T)/V(C)
Variable	Treated	Control	%bias	t	$p>\lvert t\rvert$	
MinuteId	3.557	3.551	0.500	0.190	0.848	0.960
LnGas	11.816	11.820	-1.500	-0.550	0.583	0.38*
LnAvgMints	2.043	2.030	0.900	0.340	0.732	1.24*
LnAvgPurchases	0.899	0.908	-0.700	-0.280	0.783	1.30*
LnAvgSales	1.679	1.688	-0.600	-0.230	0.816	1.22*
LnAvgListing	1.876	1.940	-4.100	-1.510	0.132	1.21*
LnAvgTransfers	1.414	1.412	0.100	0.050	0.962	1.21*

Table A2. Balance Check for CBPS

	Type	Diff.Adj	M.Threshold	V.Ratio.Adj	
prop.score	Distance	0.0006	Balanced,	<0.05	0.9703
LnAvgMints	Contin.	-0.0069	Balanced,	<0.05	1.2324
LnAvgPurchases	Contin.	-0.0079	Balanced,	<0.05	1.3437
LnAvgSales	Contin.	-0.0104	Balanced,	<0.05	1.212
LnAvgListing	Contin.	-0.0316	Balanced,	<0.05	1.2262
LnAvgTransfers	Contin.	0.0067	Balanced,	<0.05	1.2243
LnGas	Contin.	-0.0318	Balanced,	<0.05	0.3258
BidTimeGroup1	Binary	-0.0043	Balanced,	<0.05	.
BidTimeGroup2	Binary	0.003	Balanced,	<0.05	.
BidTimeGroup3	Binary	0.0013	Balanced,	<0.05	.

Appendix B.

Table B1. Balance Check for the New CEM Sample

	Mean			t-test		V(T)/V(C)
Variable	Treated	Control	%bias	t	$p>\|t\|$	
MinuteId	3.797	3.797	0.000	0.000	1.000	1.000
LowGas	0.172	0.172	0.000	0.000	1.000	.
ModeGas	0.421	0.421	0.000	0.000	1.000	.
HighGas	0.407	0.407	0.000	0.000	1.000	.
LnAvgMints	0.805	0.791	1.500	0.260	0.794	1.010
LnAvgPurchases	0.193	0.225	-5.400	-0.960	0.336	0.980
LnAvgSales	0.475	0.468	0.800	0.140	0.889	1.030
LnAvgListing	0.526	0.534	-0.800	-0.140	0.891	1.000
LnAvgTransfers	0.482	0.495	-1.800	-0.320	0.746	1.020

Table B2. ATE Based on the New CEM Sample

Dependent variable:	LnNumSales	LnSaleAmount	LnNumSales	LnSaleAmount
Treated	-0.095**	-0.055**	-0.050*	-0.035**
	(0.047)	(0.023)	(0.030)	(0.018)
LagLnNumSales			0.337***	0.144***
			(0.027)	(0.019)
LagLnNumListings			0.110***	0.096***
			(0.018)	(0.014)
Fixed Effects on Users	Yes	Yes	Yes	Yes
Fixed Effects on Months	Yes	Yes	Yes	Yes
Observations	17,598	17,598	16,341	16,341
Num of Users	1,257	1,257	1,257	1,257
R-squared	0.511	0.518	0.610	0.597

Note: Robust standard errors clustered at the user level; * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

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