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ORIGINAL PAPER

Striking the Right Notes: Long- and Short-Term Financial Impacts of Musicians' Charity Advocacy Versus Other Signaling Types

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Abstract
By using multilevel mediation involving 322,589 posts made by 384 musicians over 104 weeks, we simultaneously analyze the short-term and long-term effects of charity-related signaling on sales, with social media engagement as the mediator. Specifically, we compare the effects of charity-related signals with those of two other types of signals: mission-related (i.e., promoting music and commercial products) and non-mission-related (i.e., other posts that do not relate to the other two categories). In the short term, the indirect effect of using charity signaling on sales (through engagement) is positive, though smaller than the effects of mission-related and non-mission related signals. However, in the long term, the indirect effect of regularly using charity-related signaling on sales (through long-term engagement) is greater than for the effects involving the other types of signals. We derive from these findings three main implications for the business ethics literature. First, in the long term, the mutual economic benefits of charity signaling should encourage both entities (i.e., musicians and charities) to go beyond short-term, transactional philanthropy. Second, because it is profitable for musicians to partner with charities in the long-term, our research argues that charities have extensive bargaining power in such co-branding decisions. Third, our research highlights the importance of studying the longitudinal aspects of co-branding decisions involving non-profit organizations; the financial outlook of such decisions could greatly vary depending on the timeframe (i.e., short vs. long).

Keywords Human brands · Musicians · Charity · CSR · Social media · Engagement · Financial performance · Multilevel analyses

Introduction

For-profit companies enter partnerships with non-profit organizations or create their own charity entities for many different reasons. For instance, such associations can allow firms to promote their own products while engaging in social causes, which are close to their heart and endorsed by their target audiences (Vanhamme et al., 2012). Such partnerships can also be a way for firms to show that "they care" about their environment and stakeholders (Adkins, 1999). Although signaling support for charity has been shown to have a positive impact on financial performance (Hasan et al., 2018), organizational legitimacy (Liston-Heyes & Liu, 2010) and stakeholder involvement (Liu et al., 2010), it remains to be seen how charity-related signals fare compared to other signals, which are more closely related to firms' core business and mission (Connelly et al., 2011; Guo & Saxton, 2014).

To better understand this issue, here is an example with the LEGO Group using different types of signals. When LEGO showcases children's creativeness through the usage of its products, it uses a *mission-related signal* that is directly linked to its core business (Guo & Saxton, 2014). In turn, LEGO also employs *charity-related signals* when it publicizes its collaboration with sight-loss organisations; in these partnerships, the LEGO Foundation freely provides blocks with Braille numbers and letters (Dixon, 2019). In this LEGO case, which signal—between the charity-related or the mission-related one—would be the most effective at

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generating engagement and sales? To the best of our knowledge, it is unknown whether the impact of charity signals on financial performance would be greater or smaller compared to the effects of other signals (Connelly et al., 2011). Given this general gap, the broad purpose of our research is to examine the different effects of charity signals versus other signals—related to a brand's mission (Guo & Saxton, 2014), for instance—on the sales made by human brands, such as musicians.

Compared with corporate brands, research on human brands is emerging (Osorio et al., 2020). This context is of special interest because musicians have been known to support numerous charities on social media. Although some research has examined the phenomenon of celebrity philanthropy on social media (e.g., Bennett, 2014; Dieter & Kumar, 2008), it is unclear if musicians and charities mutually benefit from their partnerships in financial terms (Santos et al., 2019). Documenting this issue is important for both entities. Indeed, musicians need to have a better understanding of the effects of their public advocacy and the potential frictions that could exist between their economic interests and their social responsibilities (Harlow & Benbrook, 2019). In addition, if such associations are profitable for musicians, this situation could position charities as valuable "business partners," which may have more leverage than is often assumed.

In light of these two gaps—that is, (1) contrasting charity signaling with other signals and (2) understanding the financial effects of charity signaling for musicians—our research answers the following three questions. First, we wonder if the impact of charity signaling on musicians' financial performance is larger or smaller than other types of signaling? Second, what would be the long-term and short-term effects of using charity signals on financial performance in this context? Third, does social media engagement play a mediation role to explain the different effects (short-term vs. long-term) of musicians' charity signaling on financial performance?

To answer these questions, we conducted a study with the posts (322,589 posts) and sales of 384 musicians; these data were collected over 104 weeks. In this research, we identified three main types of posts: charity-related (i.e., when artists directly discussed a given charity cause), mission-related (i.e., when artists discussed their music, shows, events or other commercial products and brands) and non-mission-related (i.e., when posts mentioned any other subjects than those belonging to the first two categories). To be able to examine simultaneously the effects of short-term versus long-term postings of different signals, we use a novel multilevel mediation recently advanced by Hayes and Rockwood (2020).

Before discussing the relevance of this method, we first define our two multilevel effects, which we label *short-term* and *long-term*. The *short-term* effect captures the average changes (in engagement or sales) from 1 week to another for a given artist (Wang and Maxwell, 2015). Because this effect captures the average longitudinal change between 2 weeks, we qualify it by using the adjective "short-term". The *long-term* effect aggregates all the information over 104 weeks for each of the 384 artists, who become the unit of analysis (Wang and Maxwell, 2015). This analysis is not longitudinal, and it uses all the information cumulated for each artist. Given these characteristics, we use the adjective "long-term" to qualify this effect (Tasca & Gallop, 2009). For simplicity of exposition, we mainly use the labels "short term" and "long term" in the rest of our manuscript; the only exception is for the methods section, which requires the usage of technical terms.

The multilevel, longitudinal analyses used in this research (Preacher et al., 2010) allow estimating the long-term and short-term effects simultaneously. Differentiating these effects is important because an inability to do so could lead to biased results and inaccurate interpretations. Here is an illustration of such potential biases. For instance, people are more likely to have heart attacks while exercising (short-term effect), but those who regularly exercise over years are less likely to suffer from heart attacks (long-term effect) (Curran & Bauer, 2011). So, according to this example, people need to account for the coexistence of both effects; it would be unreasonable to focus only on the short-term effect and to recommend people to stop exercising. Applying a similar logic to our context, our multilevel analyses provide insightful responses to our three questions, and they enable us to make three specific contributions.

First, we argue that posting about charity is beneficial to sales in *the short term*, even if this effect should be weaker than those of other signals (i.e., mission-related or non-mission related). Indeed, we expect a positive effect of using a charity signal in a given week (i.e., short-term effect), although this effect should be somewhat limited. Here, we suggest that artists who occasionally support charities could still benefit a little from mentioning them. This prediction, if confirmed, could persuade hesitant artists to experiment with charity advocacy.

Second, and importantly, we posit that the *long-term effects* of regularly using charity-related signals on sales is not only positive but also greater than the long-term effects of the other types of signals (i.e., mission-related and others). This prediction, if confirmed, could be encouraging for both music artists and charities; it would show that long-term partnerships could be mutually beneficial in financial terms and possibly many other ways (e.g., societal, reputational). Testing this prediction is important; this long-term effect, if supported, would highlight the important role that charity advocacy could play over time for brand building. By developing well-crafted strategic partnerships, both musicians and non-profits could enhance their financial situation and societal impact (Austin & Seitanidi, 2012; MacDonald et al., 2002). In sum, with our first two contributions, we seek to understand when the impact of charity signals is weaker (stronger) than those of other types of signals by referring to a temporal framework. Doing so provides a deeper understanding of the complex effects of charity signaling (Wang et al., 2008).

Third, we pay special attention to understanding the process explaining the effects of signaling on sales. To do so, we argue that engagement plays an important mediation role in explaining the short-term and long-term effects of signaling (all three types) on sales. Here, engagement on social media is conceptualized as being composed of three core indicators: shares, reactions and comments (Kumar & Pansari, 2016). Although the concept of engagement has been very influential in marketing strategy (Ji et al., 2017; Kumar et al., 2010; Li et al., 2021; Soares et al., 2022), this notion has rarely been discussed in the non-profit and signaling literatures, to the best of our knowledge. Addressing this gap, we predict that the relative effects of charity-related signaling on sales (short- and long-term) are mediated by an engagement mechanism, which becomes especially strong when musicians regularly use charity signaling. Here, we seek to extend prior research that has focused mainly on the direct impact of charity-related initiatives on engagement (Kucukusta et al., 2019; Chu et al., 2020) or financial performance (van Beurden and Gössling, 2008; Clacher & Hagendorff, 2012; Kang et al., 2016). Building on this research, we integrate both streams by arguing for a sequence "charity-related posts → engagement → sales", which is tested at two levels (short- and long-term).

By making these contributions, we derive three key implications for the business ethics literature and the management of co-branding with non-profit organizations (e.g., charities). First, the long-term, mutual economic benefits of musicians' charity signaling should encourage both organizations to go beyond short-term, transactional philanthropy. Both musicians and non-profits are encouraged to build long-term partnerships that aim to co-create durable value for societies (Austin & Seitanidi, 2012); doing so would generate financial and societal benefits for both parties (Knoll & Matthes, 2017). Second, because it is profitable for musicians to partner with charities in the long term, our research argues for a change in the relational dynamics between musicians and non-profits, with charities or non-profits having extensive bargaining power in strategic co-branding decisions. Third, our research highlights the importance of studying the longitudinal aspect of co-branding decisions involving non-profit organizations. The financial outlook of such decisions could greatly vary depending on the timeframe (i.e., short vs. long term). Indeed, we find that the financial benefits of such partnership are more advantageous when considered over a long (vs. a short) period. Importantly, this long-term beneficial effect is mainly explained by a long-term engagement mechanism. To the best of our knowledge, engagement-based processes have rarely been discussed in the business ethics literature.

Theoretical Background and Hypotheses

Signals

Through their music, activities, public statements and social media messages, artists send out different types of signals (Connelly et al., 2011; Higgins & Gulati, 2006), such as their implicit and explicit emotions (Waterman, 1996), personal and social identity (MacDonald et al., 2002), and even political resistance (Street et al., 2008). Charity-related posts and other types of posts are therefore just a small part of these signals. As they wear away over time, the information asymmetry between signal senders and signal receivers also increases (Janney & Folta, 2003), especially in the presence of other conflicting signals from the musicians themselves or from other signalers (e.g., the media and social influencers). Thus, repeating the same kind of signals is important to reduce the uncertainty of the branding interpretation. Repetition also leads to the cumulative impact of consistent signals over time (Heil & Robertson, 1991), which increases their credibility in the long term (Connelly et al., 2011).

However, while the signaling literature often stresses the importance of repetition, in some cases, intermittent, short-term signals can also have their own value. Irregular signals could be more effective when they give the impression of rarity, which increases their worth in the eyes of the signal receiver (e.g., an annual instead of a monthly prize) (Phau & Prendergast, 2000). Surprise is another potential advantage of irregular signals. It garners them more attention so that they become more memorable, helping the signalers to achieve more influence (Loewenstein, 2019).

Musicians' charity-related posts share the characteristics of non-profit social media messages—that is, they provide information related to the causes, show attempts at community building and promote calls for action (Lovejoy & Saxton, 2012). Charity-related posts are thus associated with warmth (Bernritter et al., 2016), belonging to a community (Chwialkowska, 2019), and caring for others (Bernritter et al., 2016). Communities (e.g., from a book club or a church to civic engagement) ideally help members fight isolation and look after each other's well-being (Block, 2009). The sense of belonging to a social group increases meaning in an individual's life (Lambert et al., 2013).

These messages are distinct from mission-related posts (Guo & Saxton, 2014), which imply the intrinsic quality of the products and brands, such as competence (Bernritter et al., 2016; Nepomuceno et al., 2020), credibility (Erdem et al., 2006) and symbolic values (Schembri et al., 2010). They are also different from non-mission-related posts, which are self-revealing and personal (Chung & Cho, 2017; Nepomuceno et al., 2020). In the context of this research, the popularity of a musician, or their social capital (Bourdieu et al., 2003), is also a signal. A message is likely to reach more people from a well-known artist than a new singer and is also considered more credible (Guo & Saxton, 2014). Because of these distinct features, the impact of a long- or short-term posting of each type of signal can be different, even contradictory. In the next section, we explain how different signals can influence viewers' engagement on social media in the short or long term.

Signals and Engagement

Consumers use reactions, shares and comments on social media to show their *engagement* with brands (Kumar et al., 2010); these actions are instrumental to sway other users and have persuasive effects beyond social networks (Geng et al., 2020; Kumar & Pansari, 2016). Here, engagement can be viewed as playing the role of "feedback", or countersignals, to any type of message (Connelly et al., 2011; Saxton et al., 2019). As we argue more comprehensively below, the engagement mechanism is different for mission-related posts and non-mission-related posts in comparison to charity-related posts in both the short and long terms.

Belonging to a parasocial relationship—that is, a relationship that a person builds with a musician who does not personally know him or her (Gong & Li, 2017)—"true" fans closely follows musicians' careers and personal lives, and they intensively react to any of their posts, regardless their type. Compared to "casual" followers—who occasionally follow an artist—the "true" fans engage more intensively with mission-related and non-mission-related signals in the short and long terms. For these two types of signals, we expect casual followers to show some engagement with such posts, but to a much lesser extent than the fanbase. Research has found similar effects for external commercial brands supported by musicians (Aw & Labrecque, 2020). When celebrities endorse a brand, the engagement increases among followers (i.e., fanbase), while there is no effect for casual or non-followers (Song & Kim, 2020).

We argue that the engagement with charity-related posts follows a different pattern compared to the other two types of signals. We expect this because charity-related posts belong to the category "community-centric content" (Chwialkowska, 2019) and not to the "parasocial relationship" category (Gong & Li, 2017). Community-centric messages encourage interactions among consumers, thus giving them social benefits and making them feel part of a social movement (Wirtz et al., 2013). Because they are different in kind from the other two signals of interest, we predict that charity-related signals create engagement in a different manner in the *short term* versus the *long term*.

In the *short term*, a given charity-related post should produce high engagement from the "true" fanbase, as these individuals always tend to support their favorite artists. In contrast, we posit that the casual followers would show little engagement with charity-related posts in the short term. These latter followers could seriously doubt the sincerity of artists occasionally supporting a charity, and they could make negative attributions about the artists' true intentions. In this case, casual followers could infer a lack of *authenticity* in the posts (Park & Cho, 2015). Here, casual followers could discount musicians' actions and believe that they advocate a cause to gain political capital (Kane et al., 2009), public image (Babiak et al., 2012) or for tax purposes (Dieter & Kumar, 2008). Because of this ambiguity, when musicians endorse charities on an intermittent basis, casual followers are cautious in their engagement. By combining the responses of the true "fanbase" and "casual followers", we propose the following:

H1 *In the short term*, the positive effect of musicians' charity-related posts on user engagement is *weaker* than with mission-related and non-mission-related posts.

However, in the *long term*, artists' repeated charity signals and their continued advocacy of a given cause could create strong support and engagement from casual followers. By regularly displaying their support to a given cause, celebrities build up the stability of their signals and establish the authenticity of their advocacy (Moulard et al., 2015). In this case, casual followers will see these signals as being authentic, credible and truthful, and they will infer strong, positive motives from such repeated signals (Frey & Meier, 2004). In the long term, musicians' charity-related posts should attract engagement not only from their "true" fans but also from casual followers and new followers coming from different social network circles. Indeed, given the community-centric nature of charity signaling, new followers could be encouraged to be part of the movement and to engage in pro-social behaviors (Bernritter et al., 2016; Herzog & Yang, 2018). Such signals could lead "friends" of the fanbase to support a given cause, especially when pro-social actions become a frame of reference (Frey & Meier, 2004). Formally:

H2 *In the long term*, the positive effect of musicians' charity-related posts on user engagement is *stronger* than with mission-related and non-mission-related posts.

Engagement and Sales

Engagement, as a measure of the "social media capital" of musicians, contributes to their financial income or "returns"

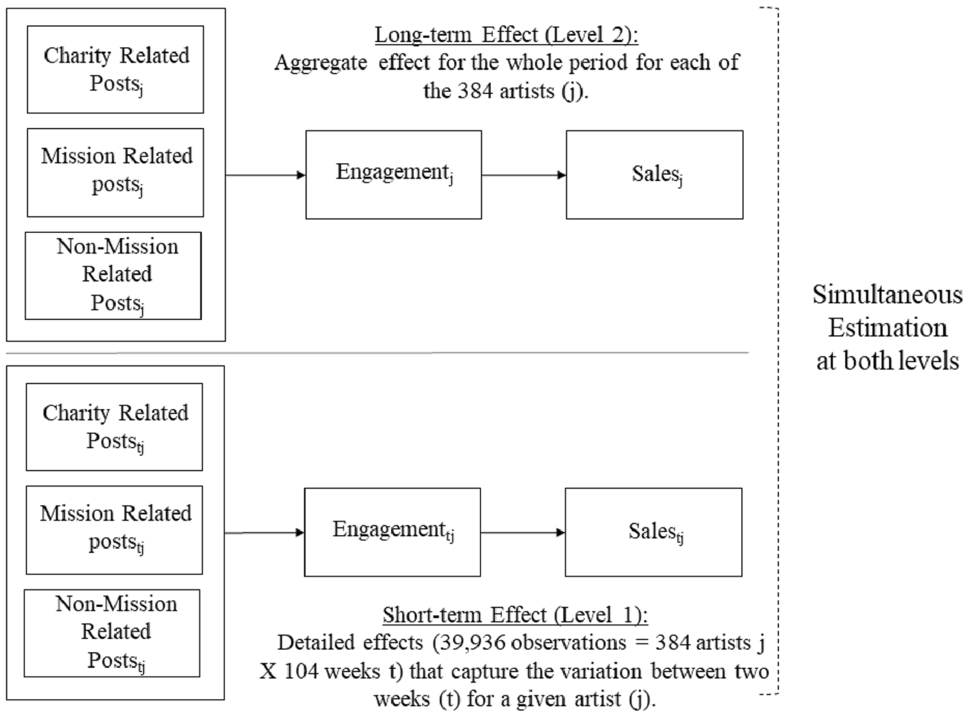

Fig. 1 Short-term and long-term impacts of different types of posts on sales through engagement

(Saxton & Guo, 2020, p. 1). For instance, the engagement on Facebook with automobile makers was associated with an increase in offline car sales (Wang et al., 2021). Similarly, the rate of social media interactions per user had a positive effect on sales in the food and beverage industry (Yost et al., 2021). For non-profit organizations, the number of Facebook shares was a key predictor of the success of a fundraising campaign (Bhati & McDonnell, 2020), and organisations with more Facebook fans also received more donations through this channel (Saxton & Wang, 2014). Building on H1 and H2, we explain in this section how engagement plays a different mediation role in the short vs. the long term (see Fig. 1).

In the *short term*, an increase in engagement helps information to reach more people in a network, which activates "latent ties" (Ellison et al., 2007, p. 1162), leading to the conversion of potential consumers. Even if this engagement takes place only intermittently, it signals a momentary rise in an artist's influence and encourages people to look for and buy his or her music (Ellison et al., 2007; Lin, 2019). Given this logic and the predicted positive effects between short-term charity-related posts and engagement, we argue that this latter construct (i.e., engagement) mediates the linkage between charity-related posts and sales. However, in the short-term, we expect that this indirect effect (i.e., "short-term charity-related posts → engagement → sales") has less amplitude than the indirect effects involving the other two short-term signals of interest (see H1 for explanations). For precision, these two comparative indirect effects are: "short-term mission-related posts → engagement → sales" and "short-term non-mission-related posts → engagement → sales". Formally:

H3 *In the short term*, the indirect effect "charity-related posts → engagement → sales" is *weaker* than similar indirect effects with mission-related posts and non-mission-related posts.

In the *long term*, when engagement is sustained over time, the growth in perceived influence is steadier, which enhances artists' competitive advantages and sales over time. The fact that strong customer engagement leads to strong sales is a key premise explaining the success of this research stream in marketing strategy (e.g., Kumar & Pansari, 2016). Since the long-term effect of charity-related posts on engagement is hypothesized to be greater than that of mission-related or non-mission-related posts over time (see H2), we argue for a similar logic for the indirect effects involving these three signals. For precision, we expect that the long-term indirect effect (i.e., "long-term number of charity-related posts → engagement → sales") has greater amplitude than the indirect effects involving the other two signals of interest (i.e., mission- and non-mission-related). Formally:

H4 *In the long term*, the indirect effect "charity-related posts → engagement → sales" is *stronger* than similar indirect effects with mission-related posts and non-mission-related posts.

Methodology

Multilevel Modeling for Longitudinal Data

The assumption of independence of observations often does not hold with data in multilevel, nested structures (Moerbeek, 2004). The first type of nested structure has members in groups. For example, for research on smoking with students grouped in schools, the smoking patterns of the students in one school could have correlations with each other because of peer influence, teacher influence and school policies (Moerbeek, 2004).

The second type of nested structure relates to different observations in individuals—such as, the physical activity of a given person measured at different times (Burton et al., 2009). Our dataset is similarly structured, and it includes 104 weekly observations for each of 384 artists. In this case, multilevel analyses evaluate how individuals change "within themselves" on average between 2 weeks (i.e., within-person effects), and how individuals differ from one another on average over the whole period (i.e., between-person effects) (Hair Jr. & Fávero, 2019). In technical terms, the *within-person effects* represent the short-term effects discussed in our theory, and the *between-person effects* capture the long-term effects previously presented.

Here are examples of within-person and between-person effects found in the literature. As an effort to capture short-term effects, Xanthopoulou et al. (2012) assessed within-person variation of employees' well-being after a short-term loss of motivation. Then, they contrasted such within-person effects with between-person effects, which conceptualized "well-being" as a "static phenomenon that can be generalized over months or even years" (Xanthopoulou et al., 2012, p. 1055). In another example related to worker performance, Minbashian and Luppino (2014) defined "short-term variability" (p. 900) as the differences caused by circumstantial events rather than "true changes" (Minbashian & Luppino, 2014, p. 900) affecting a person.

Operationalization of Constructs

Building a Weekly Dataset

Our dataset includes 322,589 posts made over 104 weeks by 384 artists. In terms of organisation, our databank includes 39,936 observations—which represent the number of weeks by artist (104 weeks * 384 artists)—in which the variable "artist" is nested with the variable week. This form of nested, multilevel databank allows simultaneous testing for "within-person" effects and "between-person" effects, which respectively correspond to the "short-term" and "long-term" effects in our theory.

Our posts originated from three platforms (Facebook, Twitter, and Instagram) and were collected for 384 artists/music groups of different nationalities over 2 years (2016, 2017). Firstly, we applied machine learning to identify the constructs we needed. The first construct demonstrated whether a post invited social media users to play an active role in social causes, in other words, whether a post was related to charity causes (Nepomuceno et al., 2020). The other three constructs are explicit selling (indicating whether a post explicitly promoted a music product or merchandise), show-related (whether a post explicitly or implicitly promoted a show) and merchandise-related (whether a post explicitly or implicitly promoted merchandise, a brand or a company for a commercial purpose).

To achieve this, we used another much smaller dataset (of 5,413 posts) already human-coded on the four variables (with three raters and an inter-rater agreement ranging from 81.8 to 97.6%; see Web Appendix A, Table A1) to train four classifying models, one for each variable. We used Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019a, 2019b), an advanced Natural Language Processing method. The results indicate 98%, 83%, 83% and 78% accuracy in predicting the presence of charity-related, explicit selling, show-related and merchandise-related posts, respectively (See Web Appendix A, Table A2).

We then applied the four models to predict the constructs on the original dataset (n = 322,589). They identified 5,168 charity-related, 53,305 explicit selling, 109,508 show-related and 21,917 merchandise-related posts. We then created a new variable called mission-related post (Guo & Saxton, 2014), namely whether a post is related to shows, merchandise, or explicit selling. In total, 141,919 posts are mission related. Finally, non-mission-related posts capture the rest of the social media posts when they are neither mission-related nor charity-related.

Next, we converted this dataset into a weekly one to merge it with Nielsen's weekly sales data, which covered album sales, digital song sales and streaming of these artists on the Canadian market in 2016 and 2017. To achieve this, we summed up the number of posts of each type for each week. Similarly, for the engagement information for different types of posts, instead of using the number of reactions (i.e., likes, love, anger, laughter, sadness, surprise, and thankfulness), comments (i.e., comments and replies) and shares (i.e., shares and retweets) for each post of each artist, we summed up the number of reactions, comments and shares for each type of post (i.e., charity-related posts, mission-related posts and non-mission-related posts) of each artist each week. The new dataset includes 39,936 weekly observations (104 weeks * 384 artists).

Table 1 Definitions of the variables

Variables	Definition	Data source
Charity-related posts$_{tj}$	The ln value of the sum of the number of charity-related posts in week t of artist j	FB, Twitter, Instagram
Charity-related posts$_j$	The mean of charity-related posts$_{tj}$ over 104 weeks for artist j	FB, Twitter, Instagram
Charity-related posts$_{tj(w)}$	Deviation of charity-related posts$_{tj}$ from charity-related posts$_j$ per week (i.e., charity-related posts$_{tj(w)}$ = charity posts$_{tj}$—charity-related posts$_j$)	FB, Twitter, Instagram
Engagement$_{tj}$	The ln value of the sum of the volume of all reaction (i.e., likes, loves, anger, laughter, sadness, surprise, thankfulness), retweets/shares, and comments/replies for artist j in week t	FB, Twitter, Instagram
Engagement$_j$	The mean of engagement$_{tj}$ (i.e., reactions$_{tj}$, shares$_{tj}$, and comments$_{tj}$) over 104 weeks for artist j	FB, Twitter, Instagram
Engagement$_{tj(w)}$	Deviation of engagement$_{tj}$ from engagement$_j$ per week (i.e., engagement$_{tj(w)}$ = engagement$_{tj}$—engagement$_j$)	FB, Twitter, Instagram
Sales$_{tj}$	The ln value of the sum of volume for album sales$_{tj}$, digital songs$_{tj}$, and streaming$_{tj}$ for artist j in week t	Nielsen
Sales$_j$	The mean of album sales$_{tj}$, digital songs$_{tj}$, and streaming$_{tj}$ over 104 weeks for artist j	Nielsen
Sales$_{tj(w)}$	Deviation of sales$_{tj}$ from sales$_j$ per week (i.e., sales$_{tj(w)}$ = sales$_{tj}$—sales$_j$)	Nielsen
Mission-related posts$_{tj}$	The ln value of the sum of the number of posts related to merchandise, shows or explicit selling of artist j in week t and 1	FB, Twitter, Instagram
Non-mission-related posts$_{tj}$	The ln value of the sum of the number of posts not related to mission or charity of artist j in week t and 1	FB, Twitter, Instagram
Fanbase size$_j$	Artist j's fanbase size: < 10 K Facebook fans (coded as 0), 10–100 K fans (1), 100 K–1 M fans (2), 1–5 M fans (3), > 5 M fans (4)	Facebook
Track volume$_{tj}$	The ln value of the sum of artist j's volume of tracks released in week t	Spotify
Tweet volume$_{tj}$	The ln value of the sum of the number of tweets mentioning artist j on Twitter in week t	Twitter
News volume$_{tj}$	The ln value of the sum of the number of news articles on an artist on Google News that week	Google News
Experience$_j$	The ln value of the sum of the number of years from when artist j's first musical product was publicly released until 2017	MusicBrainz
Age$_j$	The ln value of the sum of artist j's age until 2017	Wikipedia and press
Total track volume$_j$	The ln value of the total volume of tracks released by artist j in their career until the end of 2017	Spotify
Week$_t$	Week t (ranging from 1 to 104) of the relevant data	

Control Variables

We adopted different approaches to find the control variables. First, we used a scraping engine on Python to find news articles mentioning each artist on Google News in the titles or leads. Second, through the *application programming* interfaces (API's) of Twitter and Spotify, we accessed the tweet volume of each artist for each day, the information of their tracks and the release dates of these tracks. We then built the weekly variables for news volume (i.e., the number of articles mentioning an artist each week in the titles or leads), tweet volume (i.e., the number of tweets mentioning an artist each week) and track volume (i.e., the number of tracks featuring an artist each week). We calculated the total number of tracks over all the artists' careers until the end of 2017. Third, Facebook fanbase size information, artists' age, and their experience (i.e., the number of years from the beginning of their career until 2017) were manually collected from Facebook, MusicBrainz, Wikipedia, or past press articles. Facebook fanbase size was coded from 0 to 4: less than 10,000 Facebook fans (0), 10,000 to 100,000 fans (1), 100,000 to one million fans (2), one million to 5 million fans (3) and more than 5 million fans (4). See Table 1 for definitions of all variables.

Apart from the fanbase size, all other variables were ln-transformed to remedy skewed distributions and ensure construct consistency. Collinearity is not an issue for the ln-transformed variables of the number of charity-related posts ($M = 0.07$, $SD = 0.26$), the number of mission-related posts ($M = 1$, $SD = 0.93$), and the number of non-mission-related posts ($M = 1.19$, $SD = 1$), for which correlations range from 0.13 to 0.49.

Measuring Engagement and Sales

Consumers use reactions, shares and comments on social media to show their engagement with brands and firms (Kumar et al., 2010). This conceptualization of engagement is consistent with Kumar et al.'s (2013) construct "customer influence"—that is, a key dimension of engagement (Kumar, 2018). Our conceptualization also aligns with previous research that finds strong correlations between reactions, shares and comments (Ji et al., 2017; Li et al., 2021; Soares et al., 2022).[1]

To measure music sales, we combined sales of digital songs, sales of albums (both digital and physical) and streaming. Recent literature has confirmed that streaming reflects music industry revenues (Wlömert & Papies, 2016), music consumption (Datta et al., 2018), digital music sales (Aguiar & Martens, 2016) and even physical album sales (Lee et al., 2020). While research on streaming has also found a cannibalizing effect of streaming adoption on other sales channels (e.g., Aguiar & Waldfogel, 2018; Wlömert & Papies, 2016) at the industry level, it still has a positive relationship with other types of sales at the artist and song levels (Aguiar & Waldfogel, 2018).

After the ln-transformations, the three social media engagement measures: reactions ($M=7.68$, $SD=4.59$), comments ($M=4.7$, $SD=3.2$) and shares ($M=3.99$, $SD=3.4$) achieved high correlations (between 0.81 and 0.95, $p<0.001$), high alpha, composite reliability (CR) and average variance extracted (AVE) (between 0.89 and 0.96) (See Appendix B). Thus, we created the engagement construct ($M=5.46$, $SD=3.58$) from the mean of these three ln-transformed variables.

Similarly, because of the high correlations (between 0.73 and 0.88, $p<0.001$) and high alpha, CR and AVE (between 0.81 and 0.93) of the three sales-related constructs (See Appendix B)—that is, album sales ($M=2.69$, $SD=2.2$), digital songs sales ($M=4.28$, $SD=2.68$) and streaming ($M=10.77$, $SD=3.38$)—we created the sales construct ($M=5.91$, $SD=2.58$) from the mean of these three ln-transformed measures.

Finally, we tested the two-factor structure (with sales and engagement) for longitudinal measurement invariance. The high number of waves (104), the large number of parameters, and the modest sample size for each wave (384) made it technically challenging to conduct the tests for all the waves (Kyriazos, 2018). Thus, we decided to test invariance at five equally-spaced times (weeks 20, 40, 60, 80, and 100), using Laavan in R (Mackinnon et al., 2022). Cross-sectional CFA's for each of these periods provide good fit indexes, with high alpha, CR and AVE for each latent construct (between 0.81 and 0.96) (See Web Appendix C) (Hita et al., 2022). The longitudinal measurement invariance test confirms that our repeated constructs attain configural and metric invariance (Chen, 2007; Putnick & Bornstein, 2016) over these five periods (See Web Appendix E).

Thus, all our main variables (i.e., number of charity-related posts, number of mission-related posts, number of non-mission-related posts, engagement and sales), tweet volume, news volume and track volume are measured for each week for each artist (level 1 variables). The others (i.e., fan-based size, age, total track volume and experience) are assumed to remain the same over the whole period for a given artist (level 2 variables). Explanations of each construct are available in Table 1. Because of the collinearity issue between tweet volume and fanbase size ($r=0.77$, $p<0.001$) and between age and experience ($r=0.78$, $p<0.001$), tweet volume and experience were removed from the analyses (See Web Appendix F).

Multilevel Mediation in MLmed

Central to our research is the multilevel mediation method proposed by Zhang et al. (2009). Building on this initial work, Hayes and Rockwood (2020) renamed it "multilevel conditional process analyses" and developed a macro in SPSS to help in the usage of these relatively complex analyses. The name of this macro is MLmed, for multilevel mediation, and we use it in this research. Given the multilevel structure of our data, MLmed—which relies on mixed linear modeling—is appropriate for the following reasons. MLmed accounts for the hierarchical, nested nature of our data, which is organized in two levels. Importantly, MLmed simultaneously analyzes these two types of effects by separating each observation into two parts: the average effect for each artist (i.e., between-person or long-term effect) and the average difference between 2 weeks within each artist (i.e., within-person or short-term effect). Please see the work of Hayes and Rockwood (2020) for an effective summary of this analysis.

Our weekly constructs are of level 1 and those are associated with different artists (level 2). Since our data is longitudinal (Tasca & Gallop, 2009), MLmed allows us to simultaneously analyze the effects within each artist over time (i.e., within-person effects) and the variations from artist to artist (i.e. between-subject effects). Specifically, MLmed separates the cluster mean (i.e., the average effect for each artist: the between-person effect) from the deviation to the cluster mean for each observation (i.e., the difference between an observation and the average effect for each artist: the within-person effect). At the end, this procedure allows us to analyze both effects simultaneously. In addition, MLmed calculates multilevel indirect effects between the independent variable of interest (e.g., charity-related posts), the mediator (e.g., engagement) and the dependent variable (e.g., sales); and it tests their significance by conducting Monte-Carlo

[1] In addition to the conceptual reasons for aggregating reactions, comments and shares, there is also a conciseness reason. In our case, a concise measure is important, so we combine different sources of data in a multilevel mediation model. Cole and Preacher (2014) argue against the use of manifest variable paths because of measurement errors, especially in complex models. Accordingly, the use of latent variables formed by multiple measures is usually recommended.

Table 2 Fixed effects and indirect effects of the mediation model

Independent variables	β	t	B	t
Within effects (short-term)	On engagement$_{tj(w)}$		On sales$_{tj(w)}$	
Constant	2.79	3.64***	5.2	5.42***
Charity-related posts$_{tj(w)}$	0.73	11.1***	− 0.007	− 0.45
Mission-related posts$_{tj(w)}$	1.21	113.58***	0.16	26.08***
Non-mission-related posts$_{tj(w)}$	1.59	136.73***	0.06	7.99***
Engagement$_{tj(w)}$	–	–	0.06	22.64***
Track volume$_{tj(w)}$	− 0.05	− 1.94	0.26	20.27***
Between effects (long-term)	On engagement$_j$		On sales$_j$	
Fanbase size$_j$	1.04	20.27***	1.3	14.3***
Charity-related posts$_j$	2.13	3.97***	− 0.15	− 0.22
Mission-related posts$_j$	1.11	8.59***	0.02	1.47
Non-mission-related posts$_j$	1.65	15.55***	− 0.61	− 3.64***
Engagement$_j$	–	–	0.23	3.66***
Track volume$_j$	2.49	2.42*	− 0.85	− 0.67
Age$_j$	− 0.78	− 3.22**	0.02	0.14
Total track volume$_j$	− 0.04	− 0.82	0.16	2.54*
Charity-related posts—> Engagement—> Sales	Coefficient	Z	p value	95% CI
Within indirect effects (short-term)	0.04	9.96	< 0.001	[0.03, 0.05]
Between indirect effects (long-term)	0.49	2.65	0.008	[0.18, 0.9]

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $p < 0.1$, BIC = 240,729.9

simulations. To the best of our knowledge, MLmed is one of the rare solutions that can test the significance of multilevel indirect effects.

In a classical longitudinal model, an observation in week t belongs to an artist j (i.e., cluster j). Charity-related posts$_{tj}$ and engagement$_{tj}$ are the respective observed values of the number of charity-related posts and the level engagement in week t for artist j. Charity-related posts$_j$ and engagement$_j$ refer to the cluster averages of charity-related posts and engagement for artist j. In MLmed, the within-person effects are the differences between the observed and mean values for an artist j (Zigler & Ye, 2019). Charity-related posts$_{tj(w)}$ is the difference between charity-related posts$_{tj}$ and charity-related posts$_j$, whereas engagement $_{tj(w)}$ is equal to engagement$_{tj}$ minus engagement$_j$. Thus, charity-related posts$_{tj(w)}$ and engagement$_{tj(w)}$ capture the within-person variations effects, while charity-related posts$_j$ and engagement$_j$ show the between-person effects (Song, 2018; Zigler & Ye, 2019). Similarly, the dependent variable sales$_{tj}$ is composed of sales$_j$, which is the cluster mean, and the sales$_{tj(w)}$, which is the deviation from the cluster mean. See Table 1 for formal definitions.

Test of Hypotheses by Using MLmed

We used MLmed to test our four hypotheses (see Table 2 for an overview of the results). In terms of within-person effects (i.e., short-term effects in our theory), charity-related posts ($\beta = 0.73$, $p < 0.001$) have a positive but weaker effect on engagement compared to mission-related posts ($\beta = 1.21$, $p < 0.001$) and non-mission related posts ($\beta = 1.59$, $p < 0.001$). These effects occur at level 1. According to these results, H1 is supported.

In terms of between-person effects (i.e., the long-term effects in our theory), the effect of charity-related posts on engagement is positive and stronger ($\beta = 2.13$, $p < 0.001$) than that of mission-related posts ($\beta = 1.11$, $p < 0.001$) or non-mission related posts ($\beta = 1.65$, $p < 0.001$); these results occur at level 2. Accordingly, H2 is confirmed.

We test H3 and H4 by reporting the indirect effects of interest, as calculated by MLmed. The significance of the indirect effects is determined by using Monte-Carlo simulations (i.e., 10,000 samples) that produce 95% confidence intervals (CI).

In terms of within-person effects (i.e., short-term effects), the indirect effect "charity-related posts → engagement → sales" is positive and significant ($\beta = 0.04$, $p < 0.001$); in addition, the CI do not contain zero (95% CI [0.03, 0.05]). We also test the within-person indirect effects involving the two other signals—that is, "mission-related posts → engagement → sales" ($\beta = 0.08$, $p < 0.001$; 95% CI [0.07, 0.09]) and "non-mission-related posts → engagement → sales" ($\beta = 0.10$, $p < 0.001$; 95% CI [0.08, 0.11]). Consistent with H3, in the short term, the indirect effect

Table 3 Cross-sectional and longitudinal models on sales

Independent variables	Cross-sectional (Model 1) β	t	Longitudinal (Model 2) β	t
Within effects (short-term)	On $sales_j$		On $sales_{tj}$	
Constant	5.27	5.61***	5.27	5.61***
Charity-related $posts_{tj}$	–	–	− 0.02	− 1.32
Mission-related $posts_{tj}$	–	–	0.14	22.90***
Non-mission-related $posts_{tj}$	–	–	0.05	7.04***
$Engagement_{tj}$	–	–	0.05	21.16***
News $volume_{tj}$	–	–	0.20	21.21***
Track $volume_{tj}$	–	–	0.23	18.23***
Between effects (long-term)	On $sales_j$		On $sales_{tj}$	
Charity-related $posts_j$	0.14	0.22	0.16	0.25
Mission-related $posts_j$	0.08	0.45	− 0.07	− 0.39
Non-mission-related $posts_j$	− 0.55	− 3.34***	− 0.60	− 3.64***
$Engagement_j$	0.16	2.55*	0.11	1.71
News $volume_j$	1.51	3.86***	1.30	3.34***
Track $volume_j$	− 1.18	− 0.94	− 1.41	− 1.12
Fanbase $size_j$	1.20	12.92***	1.20	12.92***
Age_j	− 0.96	− 3.23**	− 0.96	− 3.23**
Total track $volume_j$	1.20	12.92***	0.16	2.59*

R^2 and Adjusted R^2 of Model 1 = .77; BIC of Model 2 = 93,579.05

***$p<0.001$, **$p<0.01$, *$p<0.05$, $p<0.1$

involving charity-related posts is weaker than the indirect effects involving the other two signals.

In terms of between-person effects (i.e., long-term effects), the indirect effect "charity-related posts → engagement → sales" is positive, significant and of large amplitude ($\beta = 0.49$, $p < 0.01$; 95% CI [0.18, 0.9]). The between-person indirect effects involving the other two signals—that is, "mission-related posts → engagement → sales" ($\beta = 0.26$, $p < 0.001$; 95% CI [0.11, 0.41] and "non-mission-related posts → engagement → sales" ($\beta = 0.38$, $p < 0.001$; CI [0.18, 0.60]—are also positive and significant, although of lesser amplitude than the indirect effect involving charity-related signal. These results support H4.

Additional Analyses

Direct Effects on Sales

We also test the direct effects of the different signals on the level of sales—that is, the final outcomes. First, we ran a cross-sectional regression on $sales_j$, with the cluster mean of $sales_{tj}$ for each artist being the dependent variable (Table 3, Model 1), and the cluster means of other variables for each artist being the predictive variables. This model is the equivalent of testing between-subject (long-term) effects. Here, we note that charity-related $posts_j$ are not significant on $sales_j$; neither are mission-related $posts_j$. In turn, non-mission related $posts_j$ have a negative relationship with $sales_j$ ($\beta = -0.55$, $p < 0.001$).

Second, we conducted a mixed linear regression[2] on $sales_{tj}$, including both the cluster means of other variables (for each artist) and their observed values as predictive variables (Table 3, Model 2). Both charity-related $posts_j$ (within-person, or short-term effects) and charity-related $posts_{tj}$ (between-person, or long-term effects) are not significant. For this signal, it seems that there are only indirect effects on sales through engagement in the short and long terms (see results for H3 and H4).

The effect of mission-related $posts_{tj}$ is positive in the short term ($\beta = 0.14$, $p < 0.001$), while mission-related $posts_j$ are not significant in the long term. This signal only has a direct effect on sales when it is done in the short term. In the long term, like charity-related signals, mission-related posts indirectly generate sales through engagement.

Finally, non-mission-related $posts_{tj}$ have a positive effect ($\beta = 0.05$, $p < 0.001$) in the short term, but

[2] It should be noted that the mixed linear regression model (Table 3, Model 2) used the observed values of the independent variables (e.g., charity-related $posts_{tj}$) for short-term effects. In contrast, MLmed (Table 2) applied the differences between their observed and cluster mean values (e.g., charity-related $posts_{tj(w)}$) for short-term effects.

non-mission-related posts$_j$ have a negative effect on sales$_{tj}$ ($\beta = -0.6$, $p < 0.001$) in the long term. At first sight, this result is surprising, and it will be discussed in detail in the general discussion.

Endogeneity Test

To investigate possible omitted bias linked to our charity-related posts$_{tj}$ variable, we applied Kim and Frees' (2007) generalized method of moments. This technique applies to multilevel models without requiring external instrumental variables and is implemented through the R package REndo (Gui et al., 2021). It provides a reference random effects model (REF) along with two more robust models: the generalized method of moments (GMM) and a fixed effects (FE) model. Both tests comparing between REF and FE: $x^2(11, N = 39{,}936) = 333.2$, $p < 0.001$ and between GMM and FE: $x^2(10, N = 39{,}936) = 333.1$, $p < 0.001$ are significant. This indicates that there could be omitted variable bias. However, the parameters for the three models are analogous to the third decimal. This demonstrates that while there might be an omitted variable bias, our results are not affected and can be deemed robust.

The Moderation Effect of Fanbase Size

Additionally, we ran a post hoc analysis, with fanbase size$_j$ as a moderator in the link between charity-related posts$_j$ and engagement$_j$ in the sequence "charity-related posts—engagement—sales" (i.e., between-subject, or long-term effects). The interaction between fanbase size$_j$ and charity-related posts$_j$ on engagement$_j$ is positive and significant ($\beta = 1.24$, $p < 0.05$). The 95% confidence interval for the index of moderated mediation does not contain 0 ($\beta = 1.1$, 95% CI [0.17, 2.06]) (Hayes & Rockwood, 2020)*;* this result indicates that the value of the indirect effect is different for different values of the moderators. Accordingly, we probe the indirect effects at different values of the moderating variable (Preacher et al., 2007). The long-term indirect effect of charity-related posts$_j$ on sales$_j$ is not significant when fanbase size$_j$ is less than 3, or when artists have less than one million Facebook fans. The results are significant when fanbase size$_j = 3$ (i.e., when artists have 1–5 million fans, $\beta = 1.67$, $p < 0.001$), and when fanbase size$_j = 4$, (i.e., when artists have more than 5 million fans, $\beta = 2.77$, $p < 0.001$). In other words, only when musicians have more than 1 million fans do their charity-related posts have a positive long-term indirect effect on sales through engagement. This effect increases as their fanbase increases.

Robustness Check

To confirm the validity of our measures for engagement and sales, we ran a confirmatory factor analysis (CFA) on their respective component factors in the entire dataset. Two composite variables were created from their component factors, with each factor being multiplied by its respective loading (Lefcheck, 2016). We used these new composite variables for sales and engagement and replicated our previous analyses with these new variables. All the earlier findings were replicated, confirming again H1-H4 and the moderation role of fanbase size (Web Appendix G).

General Discussion

Theoretical Implications

Despite the rich literature on the financial impact of charity initiatives and corporate social responsibility (CSR) programs, previous studies have often focused on the *direct relationship* between charity or CSR and performance indicators (e.g., Wang et al., 2008; van Beurden and Gössling, 2008; Clacher & Hagendorff, 2012; Kang et al., 2016) by accounting for the influence of factors such as size, industry (van Beurden and Gössling, 2008), marketing capability (Mishra & Modi, 2016) and geographical differences (Lu et al., 2020). A separate literature has also examined charity or CSR *engagement* on social media (e.g. Kucukusta et al., 2019; Chu et al., 2020). This second literature considers engagement as an important goal to achieve so that firms can communicate their ethical practices and enhance their reputation. While Saxton and Guo (2020) have already discussed the mediating role of "social media capital" in the linkage between "social media presence" and "organizational outcomes" (Saxton & Guo, 2020, p. 2), the current research takes an extra step by confirming the sequence *charity-related posts → engagement → sales* with field data.

Also, previous research on the impact of charity or CSR on financial performance has rarely separated short-term from long-term effects, resulting in possible biases. Some studies find a positive impact (Cai et al., 2012; Lev et al., 2009), while others report insignificant (Clacher & Hagendorff, 2012) or even negative impacts (Sipilä et al., 2021). By analyzing short-term and long-term effects simultaneously through multilevel mediation (Wang & Maxwell, 2015), we provide new insights into reconciling previous conflicting results. Indeed, we find that among musicians, charity signaling on social media does not have a significant direct effect on sales in either the short or the long term. This finding is also confirmed through cross-sectional and longitudinal models. Instead, charity signaling has a *positive indirect effect* on sales through social media engagement in the short and long terms. The indirect effect of charity signaling on sales (through engagement) is lower than the impacts of other types of signaling in the short term. Yet, in the long term, it is higher than other types of signaling, including mission signaling, despite the latter's focus on artists' core business.

While engagement drives sales, the motivations for engagement and sales are not always the same. Previous literature examined the impacts of content signals on engagement (Schreiner et al., 2021) and on sales (Babić Rosario et al., 2016; Yost et al., 2021), as well as the effect of engagement on sales (Yoon et al., 2018). The current research takes the extra step by studying three types of constructs (i.e., signals, engagement and sales) in tandem and by comparing their short-term versus long-term impacts.

For charity signaling, authenticity is important for engagement (Wymer & Akbar, 2019), which impacts sales in the long term. In this case, engagement is linked to self-identification (Chapman et al., 2020). In other words, users are engaged with causes supported by musicians in order to express their own prosocial identities (Hitlin, 2007). Signal authenticity, though related to, goes beyond signal reliability (Connelly et al., 2011). It considers the signaler's honesty and the fit between the signaler and the signals (Connelly et al., 2011), and it distinguishes the signaler from the others (Moulard et al., 2015). Charity signaling could thus be a powerful channel to distinguish brands. Previous literature has already examined philanthropy and CSR for brands' legitimacy building (Sánchez, 2000; Werther & Chandler, 2005). By comparing the long-term impact of charity signaling versus other signaling types on sales, we showcase its strategic potential.

We note that non-mission signaling has significant direct effects on sales in the short and long terms, though in opposite directions. That is, the short-term direct effect of non-mission signaling on sales is positive, but its long-term direct effect is negative. We explain this surprising result by arguing that the authenticity of non-mission related signals may decrease with repetition, which is the opposite for charity signaling. Non-mission-related signals can be the positions that artists take on different issues, such as their thoughts on current events, politics, sports, or society, or simply moments in their own lives. The rarity (Moulard et al., 2015) and spontaneity (Kreling et al., 2022) of such signals, rather than their regularity, may make them more authentic. However, the abundance of artists' messages on their personal lives and experiences over time could make the messages come across as planned and framed, which would result in less perceived authenticity and lower sales (Kreling et al., 2022).

Our research also contributes to the non-profit literature. Research on charity donations often focuses on the direct connections between the non-profits and their donors (Kumar & Chakrabarti, 2023). By studying charity-advocating artists, we contribute to the understanding of the actors in the non-profit-related network by examining the role of an additional intermediary (i.e., supporting artists). The exploration of a finer-grained conceptualization of the different actors involved in charity donation is important as non-profit research keeps growing as a field.

Managerial Implications

Given the importance of charity signaling on sales, musicians would benefit from making it a part of their long-term branding strategy. The public's scrutiny of celebrities (Dieter & Kumar, 2008; Duvall, 2015; Haynes, 2014) could make them hesitate to voice their advocacy. Even in the short term, when its indirect impact is modest, charity signaling already contributes to sales. This contribution becomes greater over time when the signals are consistent. It should be noted that only when artists achieve significant stardom will charity signaling help their engagement and sales in the long run. Future research could examine human brands in different areas—such as entertainment, fashion and sports—to see whether the findings are valid in other contexts and industries. Furthermore, scholars could also examine possible circumstances where charity signaling is an effective long-term branding channel for smaller brands.

Also, while previous literature has stressed the importance of bonding with consumers through content marketing (Geng et al., 2020), we show that self-revealing actions by artists should be done with care because of their negative impact on sales over time, as their authenticity may weaken in the long term. This is the case observed for non-mission-related signals. For corporate brands, the bonding mechanism and authenticity perception might not follow the same pattern (Napoli et al., 2014). Authenticity in corporate brands (Södergren, 2021) refers to at least one of three aspects: brands' honesty (Morhart et al., 2015), consumers' emotional attachment to them (Beverland, 2005) and their history as cultural icons (Holt, 2004). Even for humanized corporate brands, consumers perceive them through brand stimuli (e.g., logos, slogans and interactions) and their own individual inferences (Sharma & Rahman, 2022). Thus, future research could investigate the long-term impact of non-mission-related signaling among corporate brands. The choice of stimuli, decisions on content, interactions and consumers' expectations could all influence perceptions of authenticity over time.

Our research also has managerial implications for non-profits. Their partnerships with celebrities tend to stop at the philanthropic (e.g., Thrall et al., 2008) and transaction (e.g., volunteering, Thamaraiselvan et al., 2017) levels (Austin & Seitanidi, 2012). Weak partnerships could lead to criticisms of inefficiency (Kane et al., 2009; Dieter & Kumar, 2008;

Duvall, 2015). Even though artists have plenty of good will and connections, they may lack the necessary expertise on issues and the required magnitude of activism (Alexander, 2013; Bennett, 2014; Haynes, 2014). However, with their long-term economic self-interest linked to the social good, artists will be more motivated to co-create values with non-profits (Schiller & Almog-Bar, 2013). In other words, there is potential for higher-level partnerships to ensure sustainable results for both artists and charities. Future research could also study options for such partnerships. Examples are transformative partnerships (Austin & Seitanidi, 2012) or partnerships with more than one non-profit or more than one celebrity to maximize each partner's strengths.

Future Research Avenues and Limitations

The link between charity advocacy and artists' long-term economic interests also means that non-profits could be in the position to be more selective about co-branding celebrities. In addition, smaller non-profits with unique value offerings could also benefit, as artists will need to choose the causes they truly care about in long-term partnerships, rather than selecting well-known charities for short-term publicity. Such diverse dynamics could also be a promising area for research. As artists wish to distinguish themselves in terms of charity advocacy, and as non-profits have increasing bargaining powers, the partnerships between these two entities are likely to become much more complex in years to come.

A popular aspect in the co-branding literature is the fit between celebrities and non-profit causes because of its effect on perceived authenticity (e.g., Ilicic & Baxter, 2014; Park & Cho, 2015). This "fit" could change over time, as continuous active support by celebrities could improve perceived fit. Future research could compare the impact of such changes on non-profit donations when the fit stays static versus changes over time. Here, a strengthening fit, rather than the non-changing fit, could indicate the growing influence of a cause, which, in turn, could generate more donations. Similarly, the fit could weaken over time, when for example, the celebrities change their priorities. In co-branding relationships with more than one celebrity, how might the presence of both weakening and strengthening celebrity-cause fits influence donations? Answering these questions might help non-profits to better prepare their strategies.

While we focus on charity-advocating artists, other scholars could investigate the multi-actor network which is built around non-profits. For instance, future research could examine the role of social influencers for or against a cause, corporate partners, celebrity partners, governments, experts, consumers, and of course, non-profits (Van Royen et al., 2022). The examination of topics related to multilateral exchanges, benefits and conflicts, network hierarchy, and simultaneous and sequential actions (Bruijn & Heuvelhof, 2018) could produce rich findings insights for non-profits. Future research could also examine how artists can influence the norms linked to a non-profit (Kumar & Chakrabarti, 2023) in the context of diverse and conflicting discourses. The impact of artists could become more prominent if they strengthen their partnerships with non-profits in a way that goes beyond simple awareness-raising. Building such partnerships would require that non-profits effectively coordinate the roles of their partners at different stages of their relationship over time.

Despite the numerous calls to disentangle long-term and short-term effects (Kim, 2010), we are not aware of any established procedures and analyses to do so, especially when using archival or observational data. For example, Farahani et al. (2009) interpreted the long-term and short-term effects with the same regression model, using the coefficient of the current independent variable (short-term) and the lagged effects for the last 5 years (long-term). In turn, Malliet et al. (2020) applied the Computable General Equilibrium—that is, a country-level econometric model. Then, Bhagwat et al. (2020) used separate constructs: stock market reactions for short-term and annual sales growths for long-term financial impacts. Our approach—relying on mixed modeling and MLmed—is aligned with recent analytical efforts that aim to overcome the disadvantages of archival data (Jones, 2010); in that regard, our work belongs to the growing stream of research using multi-level models in behavioral psychology (Zhang et al., 2009; Curran & Bauer, 2011; Wang & Maxwell, 2015; Brandt & Morgan, 2022). To compare different models from different paradigms, we invite methodologists to develop standardized and consistent labels and procedures. At this moment, it is difficult to identify the best practices when it is time to differentiate short-term and long-term effects.

Related to the above-mentioned limitation, we created composite variables for engagement and sales by combining archival variables. A potential issue with this approach is our inability to capture the latent construct of interest; MLmed does not allow conceptualizing latent variables and accounting for measurement errors. This issue, also named factor indeterminacy, could limit the generalizability of the models in new contexts (Rigdon et al., 2019). Future research could identify solutions, while still maintaining the advantages of using Mlmed and combining given variables into broader constructs.

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Declarations

Conflict of interest All authors have no competing interests associated with this research.

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