Spontaneous charitable donations in Sweden before and after COVID: A natural experiment

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Funding information
Vetenskapsrådet; Swedish Research Council, Grant/Award Number: 2017-01827

Abstract
Did the outbreak of COVID-19 influence spontaneous donation behavior? To investigate this, we conducted a natural experiment on real donation data. We analyzed the absolute amount, and the proportion of total payments, donated by individuals to charitable organizations via Swish—a widely used mobile online payment application through which most Swedes prefer to make their donations to charity—each day of 2019 and 2020. Spontaneous charitable donations were operationalized as Swish-payments to numbers starting with 90, as this number is a nationally acknowledged quality control label that is provided to all fundraising operations that are monitored by the Swedish Fundraising Control. The results show that the Swish-donations fluctuated substantially depending on season (less donations in January–February and during the summer months, and more donations in April–May and during the last months of the year) and specific events (peaks in Swish-donations often coincided with televised charity fundraising galas). Interrupted time-series analyses revealed that spontaneous donations were overall unaffected by the pandemic outbreak.

KEYWORDS
autoregressive integrated moving average, charitable donations through mobile payments, COVID-19, ingroup- and outgroup-charities, interrupted time series, natural experiment, Scrooge effect, Swish

1 | INTRODUCTION

The COVID-19 pandemic affected everyone when it hit the world in early 2020. The fundraising sector is no exception, and there were early concerns regarding how charitable giving would be affected by an increasing spread of the virus, hospitals filled to the brim with COVID-19 patients, and national lock-downs. A survey conducted by the Swedish Fundraising Association during the first weeks of the pandemic found that 80% of the charitable organizations had to adjust their fundraising work and 20% had to furlough some of their personnel (GIVA Sverige, 2020). The same survey revealed that 55% of the organizations predicted that donations from the public would decrease, whereas only 2% predicted that donations would increase as a result of the pandemic.

Our research objective was to test the accuracy of these predictions, and to reach this we used a natural experiment to investigate how spontaneous donations to charitable organizations in Sweden were affected by the national outbreak of the pandemic in mid-March 2020. Specifically, we analyzed weekly amounts donated to charity through Swish—a mobile payment application used by over 7.9 million private users (≈78% of the Swedish population) as of May 2021 (Swish, 2021a). Looking at the weekly patterns of both absolute amount of Swish-donations to charity and the proportion of total Swish-payments that were directed to charitable organizations...
allowed us to investigate whether the pandemic outbreak influenced charitable donations.

1.1 | Theory: Why should a pandemic influence charity?

This research is ultimately exploratory and data-driven. Still, there are theoretical accounts that could explain both a decreased and an increased level of charitable giving after the pandemic had begun.

The most straightforward explanation for a potential decrease in charitable giving is that the pandemic increased occupational, financial, and existential uncertainty and stress (e.g., Brown et al., 2020; Morgan & Boxall, 2020; Tang et al., 2021). In times of uncertainty, people tend to focus primarily on satisfying the basic physiological and psychological needs for themselves and their family, that is, the focus is on survival rather than self-transcendence. Helping strangers by donating to charitable organizations represents more “modern” needs that, at least to some extent, are related to self-esteem and self-realization (Andreoni, 1990; Duncan, 2004; Harbaugh, 1998). According to this line of thinking, we help strangers primarily when our basic needs are met, and if the outbreak of the pandemic threatened the satisfaction of these needs, then this should have decreased charitable giving at the time of the outbreak, at least among small-scale donors (Johnson et al., 2020). Consistent with this conjecture, a survey study conducted in the UK found that 53% of the participating charity organizations reported less donations whereas only 18% reported more donations during the first months of the pandemic (Charities Aid Foundation, 2020).

There are also factors that could be expected to increase individual donations after a pandemic outbreak. A pandemic is a type of natural disaster, but unlike most disasters, the COVID-19 pandemic affected the whole world at once and may therefore have stimulated the feeling of “global common fate” or “being in this together”, which could stimulate donations do charity (James & Zagelka, 2017; Zagelka, 2021). Moreover, the bombardment of information about the death rates in different countries and regions may have played a role too, because high mortality rates (but not high numbers of people in need) have been linked to increased giving (Evangelidis & van den Bergh, 2013). In a similar vein, Terror Management Theory (Greenberg et al., 1986; Pyszczynski et al., 2020) suggests that when people are reminded of their own mortality, they need to regulate their fear of death. The fact that the pandemic led to a large increase in the number of written wills (Funck, 2020) suggests that it has indeed reminded people of their mortality and propelled them to regulate their fear of death. This can be accomplished either through proximal defenses, such as denying or downplaying the risks, or alternatively by taking extreme measures to avoid being infected, or through distal defenses, such as focusing on what is most important in life and trying to improve one’s legacy, in order to strengthen the sense of meaning in life and personal significance (Syropoulos & Markowitz, 2021). Before the pandemic, this could involve spending more time with family, protesting social injustices, or doing more volunteer work. With physical distancing regulations (or recommendations in the Swedish case) in place, these behaviors are prevented but donating money to charitable causes is not. Furthermore, research has suggested that reminders of mortality tend to make people behave more in line with prosocial values (and other normative cultural values) even absent pandemic regulations (Hirschberger et al., 2008). The tendency to act more prosocially and to gain more satisfaction from helping after being reminded of one’s mortality has been termed “the Scrooge effect” (Jonas et al., 2002; Zaleskiewicz et al., 2015).

1.2 | Scope of the article: Individual donations through mobile payment systems

The current study focuses on donations made by private individuals through mobile payment systems. Although donations made by corporations, independent foundations, and high-net-value philanthropists are crucial for the charity sector as a whole (they make up the majority of the collected funds in many countries, Sato et al., 2020), the aim of the current research was to investigate how the pandemic outbreak affected donations made by private individuals.

The main reason that we focus on donations made through mobile payment systems is that this is the best way to assess spontaneous giving, in which the decision to donate and the donation occur almost at the same time. By contrast, the decision to donate and the donation are temporally separated for other popular methods of donating (e.g., a fixed donation plan that deducts a specified sum from your bank account each month, for which the decision to donate was initiated at an earlier time). Furthermore, an additional advantage of focusing on charitable donations made through mobile payment systems is that the mean amount of these donations is relatively low, which means that the daily donation amount is a reasonably good proxy for the number of unique donations that day. Infrequent but huge one-time donations made by corporations and rich philanthropists would reduce the correlation between donation amount and unique donations, but these massive donations are unlikely to be made through mobile payment platforms as the maximum amount that can be donated through one payment is relatively low.

1.2.1 | Swish

Sweden is one of the most suitable countries in the world for this kind of study, because high-quality data on charitable donations made through Swish is available. Swish is a Swedish mobile online payment application (available for Android and iOS) that was released in December 2012 (see www.swish.nu). Swish was originally intended for peer-to-peer payments, but since 2014 it is also used for customer-to-business payments, and it is increasingly used for online shopping. Swish was initiated by six of the largest banks in Sweden in order to enable people to quickly make small payments to each other without using cash or having to exchange bank account numbers.
(Swish, 2019a). The Swish application allows users to make immediate payments to each other using their smartphones. Each user’s personal bank account is linked to his or her phone number and to transfer money, the user making the payment inserts the recipient’s phone number and the amount to pay (or scans a QR-code) and identifies him- or herself with another mobile application called Bank-ID that is issued by all Swedish banks. It takes no more than a few seconds to complete a payment and the money is immediately transferred from the payer’s bank account to the recipient’s bank account. The banks are free to adjust details such as fees and the maximum amount possible to transfer, but transactions over 10,000–15,000 SEK ($1100–1650) typically require customers to log into their bank’s website or application and confirm the payment. This means that the amount donated through Swish each day tells us a lot about the website or application and confirm the payment. This means that the organization follows the rules set out by the Swedish fundraising control: no more than 25% of the raised funds can be used for administration and fundraising, individuals in charge of the organization must have no record of non-payment, and the organization must submit an annual report that is analyzed and controlled by the Swedish fundraising control. New organizations can apply for a new 90-account, but they can also lose their right to use a 90-account if they do not comply with the abovementioned rules. News about new organizations and excluded organizations are posted on the website of the Swedish fundraising control (www.insamlingskontroll.se).

Because 90-accounts are so highly renowned, all of the relatively large (and most of the relatively small) charity organizations in Sweden have such accounts and they use these accounts when they solicit donations. This implies that Swish-payments to 90-numbers make up a very good approximation of spontaneous donations to charitable causes in Sweden. The data used for this research included the amount of money (1SEK ≈ 0.10 ≈ 0.08 ≈ $0.11) that was “Swished” to 90-numbers (and to other numbers unrelated to charity) each day in 2019 and 2020.

1.3 | Quasi-experimental design

This research used an interrupted time series design. This is one of the most powerful types of quasi-experimental design that can be used to assess the presence of causal effects when a true experiment is not possible to perform. This is true particularly when the number of observations is high (more than 100 is a common desideratum) and the observations are highly reliable (Cook et al., 2002)—two conditions that were clearly satisfied in the current research. An additional advantage of this design is that it provides information concerning not just the presence or absence of a causal influence but also the specific form of the effect. For instance, it can shed light on whether the effect is abrupt (a change in the intercept), whether it gradually diffuses in the population over time (a change in the slope), or whether the observations become more fluctuating (a change in variance) or irregular (a change in cyclicity) after the breakpoint.

In contrast to a standard experiment, which compares the same or different participants between conditions, an interrupted time series analyses compares sets of observations made in two different time periods before and after an intervention or a significant natural event that is thought to have causally influenced the observed quantities. In the current research, two different breakpoints were used. First, we compared observations from 2019 with observations from 2020 to make sure that seasonal fluctuations in donations over the year would not affect the results. Second, we compared observations before and after March 16, 2020, which was when the Swedish Public Health Agency officially issued recommendations to work from home...
and avoid meeting the elderly (Folkhälsomyndigheten, 2020) and 5 days after the World Health Organization had declared that COVID-19 could be characterized as a pandemic (World Health Organization, 2020). To make the latter two time periods more comparable, we specified the first time period to start March 16, 2019.

The overarching purpose of the research was to investigate how the pandemic affected spontaneous charitable giving in Sweden by analyzing changes in the pattern of Swish-donations to charitable organizations between the aforementioned breakpoints. To take the possibility that Swish-payments overall could have changed into account, we investigated changes both in the total amounts of donations to charity organizations and in the proportions of total Swish payments that were directed to such organizations. This is important because Swish is still gaining in popularity and an increase in absolute Swish-donations could be explained by the fact that the number of people using Swish increases every year.

2 | METHOD

2.1 | Data

We obtained data from a contact person at GetSwish AB – a private company owned by the six large banks in Sweden that founded Swish. The data consisted of the daily amounts sent by Swish during the period January 1, 2019 to December 31, 2020. The Swish-payments were divided into three types of transactions: (a) P2P (“peer-to-peer”)—payments between two individuals (b) C2B (“consumer-to-business”)—payments from individuals (customers) to business owners and (c) Charity—payments from individuals (donors) to charitable organizations with a 90-account. The obtained data includes no information about the identity of the individuals who sent the payments or about the organizations that received them, and no information about the unique number of donations.

2.2 | Statistical analyses

Statistical analysis of time-series data is complex and technical. We briefly explain the techniques in a relatively simple manner in the section “Modeling time series”, which should be accessible to—and instructive for—readers who are not familiar with time series analysis. Thereafter, we describe our implementation of these techniques in the section “Implementation”, which contains more technical detail. Readers who are experts on time series analysis may skip the former section, and readers who are primarily interested in the conclusions of the research may skip the latter section or both sections.

2.2.1 | Modeling time series

One of the challenges in time-series analysis is that the observations frequently exhibit autocorrelation (cyclic or non-cyclic), which means that the signal correlates with itself at a given lag (i.e., at future time points). In other words, autocorrelation means that an observation we make today is correlated with observations made in the preceding days (or at the same time last year in the case there is cyclicity)—for instance, the temperature today is predicted by the temperature yesterday in case there is a significant autocorrelation at lag 1. The presence of such autocorrelations represents a violation of the assumption that the observations are statistically independent of each other, which classical regression models rest upon (Hillmer & Wei, 1991). Therefore, other kinds of statistical techniques that can appropriately model autocorrelation are needed. In the current research, we based the analyses mainly on autoregressive integrated moving average (ARIMA) models, which are commonly used in time-series analyses and particularly in intervention designs (Beard et al., 2019; Little, 2013).

An ARIMA model is a generalization of an autoregressive moving average (ARMA) model, in which the observed values have been replaced with the difference between their values and values from previous time points (i.e., “differencing” has been performed). The AR (AutoRegressive) part means that the outcome variable is modeled as a linear function of its own values from previous timepoints. The moving average (MA) part means that the error term is a linear combination of error terms from previous timepoints. While standard ARMA models require the processes to be stationary (i.e., with mean and variance constant across time), the ARIMA framework can handle so called stochastic trends in the data. A stochastic trend is a random function of time, in which observations depend on prior observations plus a random coefficient (“white noise”)—for instance, observations of the weather contain a random component and therefore exhibit a stochastic trend. Differencing the integrated processes forces them to become stationary (Kwiatkowski et al., 1992; Stadnitska, 2010)—this is the I (Integrated) part of ARIMA models. For instance, if the weather varies stochastically, the differences from 1 day to the next will by definition vary randomly (i.e., the differenced time series will be stationary since the differencing removes all variation except for the white noise).

Time series can also exhibit so called deterministic trends. A deterministic trend is a non-random function of time, such as a constant linear increase. Note that this is a purely mathematical concept that has nothing to do with causal determinism in the context of time series analyses. A deterministic trend is usually investigated by fitting a linear model to the data, and, in case there is such a trend, detrending is achieved by extracting the residuals of the fitted linear model—that is, we analyze the variation that is left when the trend has been filtered out (Little, 2013). The reason that we need to detrend the data in this manner is that a deterministic trend makes the time series non-stationary (as it entails a change in mean values over time), and detrending removes this non-stationarity.

More generally, removing stochastic and deterministic trends from the data allows us to isolate the signal from all the background noise in the data. Similarly, cyclic patterns in the time series can be dealt with through a statistical process called decomposition, in which seasonal components are separated from other components of the
time series (Cleveland et al., 1990). This prevents confounding between different kinds of trends in the data.

2.2.2 Implementation

In line with this standard approach, we fitted linear models over the processes to test for the presence of putative deterministic trends, which were filtered out through detrending (i.e., extracting the residuals of the fitted model as explained above) right after. We thereafter performed model identification by iteratively changing AR, I, and MA indexes through the “auto.arima” function of the “forecast” package in R (Hyndman & Khandakar, 2008) and selecting the model with the best fit assessed in terms of the AIC (Akaike Information Criterion). This procedure investigates how many time steps back we need to go (if any) in the differencing of the time series and in computing the MA and autoregressive components in order to optimize stationarity and thereby optimally isolate potential trends we are interested in from background noise in the data.

For studying the presence of autocorrelations in the processes, we computed the autocorrelation function and subsequently inspected, at a higher level of granularity, the presence of possible trends or seasonal effects by decomposing the time series into trend, seasonal, and remainder components (Cleveland et al., 1990). In order to do so, we used the MSTL (multiple seasonal trend decomposition using Loess) algorithm, implemented in R through the “forecast” package.

For understanding if and how the mean and the variance of each process changed over time, we used Pruned Exact Linear Time (PELT) algorithms. PELT finds where structural breaks are likely to be present by minimizing a cost function (i.e., minimizing predictive inaccuracies) over all possible changepoints (Dorcas Wambui, 2015). In R, these calculations are possible through the package “changepoint” (Killick, 2014), specifically by using the “cpt.mean” and “cpt.var” functions for changes in the mean and the variance respectively. The output of these functions can tell us where potential changepoints are localized, which is essential for understanding the dynamics of the investigated processes at a deeper level. This explorative approach was used for analyzing both the entire time-series and the trimmed processes before and after each of the a priori specified breakpoints (i.e., January 1, 2020 and March 16, 2020).

In order to address our research questions, we thereafter proceeded with two common approaches. First, we used forecasting-based ARIMA models (Wang et al., 2013) for predicting the observations of the second halves of the observations based on the first halves (2020 from 2019 and pandemic from pre-pandemic observations). Second, we used regression with ARIMA errors and external regressors over the entire time series (Anggraeni et al., 2017; Ling et al., 2019; Pankratz, 1991) in order to test whether there was a statistically significant change in the processes before and after the two specified breakpoints.

The logic behind the first approach is explained by Linden (2018). The main idea is to fit a model based on the observed data (the “training set”) and to compute out-of-sample forecasts up to a given number of steps ahead in the process. The time-series of the predicted values (the “counterfactual set”) is then compared to the actual out-of-sample observed values (the “test set”). If the forecasting method is capable of capturing a high portion of the variance of the future values (i.e., the counterfactual set is similar to the test set), then this would mean the model fitted to the training set is valid for describing the ongoing dynamics of the process. In case an external event had exerted a significant impact on the data generating process, the best model fitted to our training set would not be capable of producing an accurate forecast. In this case, the process dynamics would have significantly changed. Whether this is the case or not can be assessed both in terms of a graphical comparison of the forecasted values with the observed values and in terms of fit statistics. With respect to fit statistics, we report the normalized root-mean-square-error (NRMSE) and the mean absolute scaled error (MASE). The reason we chose the first is that RMSE is influenced by the scaling of the variables and therefore does not allow a proper comparison when measurement units differ across samples, while NRMSE overcomes this issue (Shcherbakov et al., 2013) and also facilitates interpretation by virtue of being expressed in percentages. MASE was instead preferred over MAPE (Mean Absolute Percentage Error) considering that the values we obtained were near 0 and MAPE is known to be systematically biased in this case (Hyndman & Koehler, 2006).

The second approach allowed us to perform formal statistical tests of whether the pandemic exerted a significant effect on donation behavior. Specifically, we added a covariate encoding the pandemic effect to the models: we created a dummy variable, with values equal to 0 for each time-step prior to the supposed change-point and 1 afterwards, as often done in intervention studies (Hamaker & Dolan, 2009; Makridakis et al., 2020). This allowed us to test whether the dummy coefficients were significantly different from zero, by computing t-statistics (the “auto.arima” function of the “forecast” package in R estimates a regression with ARIMA errors when covariates are added to the model [Hyndman & Khandakar, 2008], which facilitates interpretation by allowing us to infer whether significant changes occurred after a relevant event). Thereafter, we performed a Granger (1988) test of the association between the investigated processes (both non-transformed and seasonally adjusted) and the dummy variable for each breakpoint option, in order to further test whether the time-series had undergone a significant change from the breakpoints and onward. The Granger test is performed by running a Vector Autoregression (VAR) between two processes that are supposed to be related in time. When the lagged cross-correlation between the two processes is statistically significant and A precedes B, A is commonly said to “granger-cause” B (Leamer, 1985). If the pandemic outbreak would granger-cause a difference in donations to charity, this would mean that a variable encoding the pandemic outbreak would carry unique information about the amounts of donations to charity after the pandemic outbreak above and beyond the information provided by donations to charity prior to the pandemic. However, to conclude that the pandemic de facto had a causal impact on donations, it is of course still necessary to rule out the possibility that the association is spurious, by considering plausible alternative explanations (Eichler, 2007, 2013). In other words, the Granger test (or any other statistical test for that matter) is not a sufficient basis for making causal inferences. It may therefore be more appropriate to use the term “granger-predict” than the term “granger-cause.”
Because we noticed complex seasonal patterns could have been present (e.g., with higher donations in the late spring and winter, after payday, or during major fundraising events), both at the level of the entire processes and the trimmed ones (i.e., before and after the breakpoints), we compared three modeling techniques. We first fit simple ARIMA models over the series, by not treating the observed autocorrelations as indicators of a seasonal pattern, but rather as noise. Second, we adopted two different approaches for dealing with possible periodic effects: we fitted ARIMA models over the seasonally detrended and subsequent analyses were undergone net of the seasonalizing was achieved through the function “seasadj” in R (Hyndman & Khandakar, 2008), which subtracts the seasonal patterns estimated through the MSTS algorithm from the observations. With respect to the second technique, for choosing the optimal number of Fourier terms, we calculated all possible combinations of terms and chose the one that yielded the highest model fit assessed in terms of the AIC, as often done when this design has been implemented in the literature (Abdul-Aziz et al., 2007; Woolhiser & Roldán, 1982). In each case, for model identification, we used the “auto.arima” function of the R package forecast to automatically fit the best model over each series of observations. Utilizing all these techniques, which are advocated by different statisticians, allowed us to probe the robustness of the results to variations in the modeling.

Because we were interested in the potential influence of the pandemic outbreak on donation behavior, variations from 1 day to the next were not of fundamental interest for the analyses. In addition, analyzing daily data could be troublesome due to the presence of daily or weekly seasonality or even effects of weekends on the temporal structure of the process. For these reasons, observations for each day were aggregated into weekly averages in all aforementioned analyses. Furthermore, the forecasts we obtained by taking seasonality into account were initially shifted one lag ahead due to the fact that 2020 is a leap year (with 53 weeks). We therefore aggregated the observations for the last periods of each year so that both years would consist of 52 weeks, which greatly improved forecasting accuracy.

Because the statistical analyses were extensive, and different analyses generally yielded support for the same conclusions, we provide a summary of the results here along with open access to the complete code for performing the statistical analyses in and reproducing all the results in R and a complete description of the results: https://osf.io/bfjat/?view_only=db5f1efa86574b19b0d88e9edf005b7d.

3 | RESULTS

3.1 | Descriptive statistics

Mean daily total Swish payments, mean daily Swish donations to charity, and mean daily proportion of Swish payments that were donations to charity, for each week in 2019 (blue lines) and 2020 (red lines) are plotted in Figure 1. The pattern for total Swish payments (Figure 1, top panel) illustrates two things: (a) Swish is gaining in popularity (the red line is above the blue line), and (b) people swish more when they have more money (peaks illustrate weeks when the majority of Swedes obtain their monthly salary).

The mean daily amount that was sent to charity through Swish during these 2 years was 592,022 SEK (SD = 1,115,803; min = 147,725 SEK on February 5, 2019; max = 20,689,312 SEK on April 11, 2020). The average daily percentage of all Swish-donations that were sent to charity was 0.08% (SD = 0.18; min = 0.02% on June 6th, 2020; max = 3.84% on April 11, 2020).

It is particularly noteworthy that the patterns for 2019 and 2020 look very similar. In both years, weekly donations were lower in the beginning of the year and during the summer months and slightly higher in the late spring and in the weeks leading up to Christmas. Another aspect of the time series that sticks out is that the mean donation amount to charity (Figure 1, middle panel) and proportion of donations to charity (bottom panel) fluctuate a lot. The mean daily Swish-donation is around or below 1 million SEK for most weeks of the year, but Week 15 and Week 40 clearly stand out in both 2019 and 2020.

To understand these peaks, we probed newspapers and TV-guides from the days of the peaks. We found that the peak in Week 40 coincides with a charity gala “Children of the World” that was televised on national TV on Friday evening this week in both 2019 (October 2nd – over 9.5 million SEK donated by Swish on this single day) and 2020 (October 4th – over 16 million SEK donated by Swish). The peak in Week 15 in 2019 coincided with a traditional and very popular charity drive called “Mayflower” where schoolchildren and scouts, since 1907, sell small pins shaped as a flower to the public, and the profit goes to charitable causes benefitting children. In 2019, the Mayflower campaign launched on April 11th, and for the first time ever, buyers (including the Swedish queen) could pay for their Mayflowers through Swish (Swish, 2019b). Swish donations during the first 4 days were 7.28 million SEK on April 11th, and 5.96, 4.12, and 2.61 million SEK respectively on April 12th, 13th, and 14th.

3.2 | Time-series analyses

3.2.1 | Specification of the models

Only total Swish-payments exhibited a deterministic trend. The process could be modeled as a straight line with a significant increasing slope, F(1, 102) = 33.47, p < 0.001. This process was thus appropriately detrended and subsequent analyses were undergone net of the trend. There was no significant deterministic trend in the time-series.
for amount of donations to charity, $F(1, 102) = 2.14, p = 0.15$, or proportion of donations to charity, $F(1, 102) < 0.001, p = 1.00$. These time-series were therefore not transformed.

The PELT algorithm confirmed that the expected value for Swish payments fluctuates periodically, as can be seen in Figure 1, with 47 significant changes for total Swish payments and 46 for donations to charity specifically (but none for proportion of donations to charity), occurring most of the times with a distance of 2–3 weeks, with the mean dropping and then rising again after 4–5 weeks. This suggests the presence of a monthly oscillatory pattern, consistent with the observation we made in the descriptive analyses above that people donated more right after they had received their monthly paycheck. Furthermore, the PELT algorithm detected five significant change-points for the variance in donations to charity and proportion of donations to charity (but not total payments), corresponding to the aforementioned charity campaigns where peaks in donations can be observed (see Figure 1). These results suggest that charity campaigns yielded a higher amount donated to charity during the pandemic than before it. From the inspection of Figure 1, we can observe that the donations to charity were higher particularly at week 40, in the presence of the televised charity campaign “An evening together” on April 11th (Radiohjälpen, 2020). This is most likely an effect of the higher number of users who had adopted Swish for making charity donations when this campaign occurred, rather than a more substantive difference in donation behavior, given that an equal discrepancy between the years cannot be observed for the proportion of payments that were sent to charity during this campaign (see Figure 1).

The autocorrelations (see Figure S1 in the supplementary results file: https://osf.io/bfjat/?view_only=db5f1efa865774b19b0d88e8edf005b7d) were significant at several lags, suggesting the presence of complex seasonal patterns. Total Swish donations had a monthly seasonality, most likely due to when people receive their paychecks. The autocorrelations for gross donations to charity and its ratio to the total had instead two significant peaks at a lag of 6 months and 1 year due to prolonged charity fundraising events, as well as an oscillatory pattern at lower time-lags, which means that there were some fluctuations in donations that were extended in time.

Decomposing and seasonally adjusting the processes allowed us to deal appropriately with these complexities. A monthly effect emerged once six-months and yearly effects were removed. We thus modified the specifications for seasonal effects by adding a monthly seasonality to obtain a better autocorrelation function for the processes and then reassessed the presence of deterministic trends. Total Swish payments exhibited a significant linear trend from January 1st 2019 to January 1, 2020, $F(1, 51) = 6.63, p = 0.013$, and for the entire period of 2020 as well, $F(1, 49) = 9.28, p = 0.004$. However, there was no significant linear trend in total Swish payments from March 2019 to March 2020, $F(1, 51) = 0.11, p = 0.75$, or from March 2020 to December 2020, $F(1, 39) = 2.41, p = 0.13$. None of the other processes exhibited a clear deterministic trend. For the period from March 2019 to March 2020, there was a marginally significant linear trend in proportion of donations to charity, $F(1, 51) = 4.20, p = 0.046$, but inspection of the plot revealed that this was probably a spurious effect due to the presence of a peak caused by a charity campaign in March.

None of the entire time series exhibited any stochastic trend. Once the time series had been split by year, none of the time periods showed any stochastic trend either, save for the percentage of donations to charity of 2019, when seasonally adjusted. When March 2020 was used as the breakpoint, only gross donation to charity from March 2020 to December 2020 showed a stochastic trend, and this occurred only when the data were deseasonalized. Most of the trimmed processes were automatically modeled as white noise.
processes, and for those that were not the maximum order of AR and MA components was equal to 1, save for percentage to charity observed from January 2020 to December 2020, which exhibited stronger temporal persistence with an AR component of 2, and total Swish payments of 2020, which was modeled as an ARIMA(1,0,2) process.

3.2.2 | Examining the research question

Results of analyses of forecasting accuracy for both breakpoints (from 2019 to 2020 and from pre-pandemic to pandemic phases) based on three different kinds of models (simple ARIMA model, seasonally adjusted model, and Fourier ARIMA model) are given in Table S1 and the similarity between forecasted 2019 and 2020 actual observations is illustrated in Figure S2 (https://osf.io/bfjat/?view_only=db5f1efa86574b19b0d88e8ef005b7d). The model run by using Fourier terms performed somewhat better than the others when assessed in both terms of the MASE and NRMSE. Only the seasonally adjusted percentage to charity in 2019 performed worse than a naïve forecasting. Overall, both the indexes and at the plots demonstrated that our models were capable of accurately forecasting the subsequent values of the series, which suggests that no substantial differences in donations through Swish occurred after the onset of the COVID pandemic.

The forecasts obtained by using the January 1, 2020 as the breakpoint were somewhat more reliable than those that used the March 16, 2020 as the breakpoint (see Table S1). That is likely explained by a linear increase in total Swish donations between January and March of both years (see Figure 1), while between March and December this is less pronounced. Once we split the time series based on the onset of the pandemic, the training set did not recognize any trend and the forecasted values were significantly lower than the observed values (see Figure S2). In this case, although the observed values were slightly higher than the forecasted values, this is likely to be an artifact induced by the greater usage of Swish during winter. Indeed, the subsequent significance tests reported below revealed that neither donations to charity nor its ratio to total Swish payments showed any significant difference before and after March 16, 2020 or January 1, 2020.

In all regression models with ARIMA errors (both when we took into account seasonal effects and when we did not), none of the dummy predictors (representing whether an observation was made before or after the breakpoint) were found to have a significant effect on total Swish payments ($p \geq 0.15$), Swish donations to charity ($p \geq 0.08$), or proportion of payments that were sent to charity ($p \geq 0.62$), which indicates the absence of a statistically significant shift in the observations subsequent to the hypothesized breakpoints.

In line with the aforementioned results, the Granger tests did not indicate any significant effect of either of the breakpoints on total Swish payments ($p \geq 0.47$), Swish donations to charity ($p \geq 0.12$), or proportion of Swish payments that were sent to charity ($p \geq 0.58$). Even when the models had been seasonally adjusted, we did not find any significant effects for total Swish payments ($p \geq 0.11$), donations to charity ($p \geq 0.41$), or the proportion of payments sent to charity ($p \geq 0.72$). The results therefore did not yield support for a Granger-predictive effect of the pandemic on donation behavior—in other words, no significant changes on donation behavior could be observed following the onset of the pandemic.

4 | DISCUSSION

The simple take-home message of this research is that spontaneous donations to charitable organizations were virtually unaffected by the COVID-19 pandemic outbreak in Sweden. We reached this conclusion by conducting sophisticated time series analyses of detailed high-quality data from the mobile payment platform Swish. Although online donations to charity fluctuated substantially as a function of time of year and especially as a function of specific fundraising drives, there were no clear indications of a decrease or an increase in charitable donations when comparing 2019 against 2020 or before against after the pandemic outbreak in Sweden.

These findings are consistent with observations from more anecdotal sources. The 2020 annual report published by the membership body for fundraising organizations in Sweden (GIVA Sverige, 2021) states that the total amount of donations (not only donations by Swish) remained stable (9.1 billion SEK in 2019; 9.2 billion SEK in 2020) and that half of the organizations submitting their fundraising data reported more donations in 2020 than in 2019 (total change +636 million SEK) whereas the other half reported less donations (total change – 509 million SEK).

The main contribution of this research stems from the quality of the data and the rigor of the analyses. Although obtaining null results may seem disappointing, it is important to bear in mind that such results have great scientific importance, particularly when they are based on rigorous methods, because they help us combat the spread of false positives (e.g., Open Science Collaboration, 2015). Unlike a lot of the previous research, we did not rely on self-reported willingness to help or on “artificial” behavior such as donations in the dictator game or symbolic charitable donations of endowed money. Instead, the results are based on retrospective data of the actual amounts donated to charity through Swish each day in 2019 and 2020. To control for the constantly increasing popularity of Swish, we also analyzed the daily proportion of all Swish payments that were sent to numbers starting with 90, as these numbers (but no other numbers) are used by certified charity organizations.

Although Swish donations only make up a portion of all charitable donations in Sweden, they arguably represent among the best available operationalization of spontaneous donations, as the decision to donate and the donation occur at the same time. Including, for instance, automatic monthly donations (where the decision to donate can occur months or years before the donation is registered) could thus dilute possible real behavioral changes that might occur because of events such as a global pandemic. The validity of measuring spontaneous giving specifically through Swish is strengthened by the unprecedented popularity of Swish as a method for making both payments in
general and donations to charity, as well as the quality control and general recognition of 90-accounts in Sweden. Furthermore, few but extraordinary large donations done by corporations or wealthy philanthropists would add undesired noise to the data, but these large donations are typically not made through Swish, which renders the data highly informative for donation behavior among most individuals. For these reasons, the approach employed in the current research for testing whether the COVID-19 pandemic influenced charitable donations has substantial advantages over other common paradigms.

4.1 | Future directions: Comparing different donors, charitable causes, countries, and types of helping

The data in the current study included no information about those who made the Swish donations (other than that they are private individuals who have a Swedish bank account), which means that we could not investigate the ways in which differences between individuals, for instance, in personality traits (e.g., Hilbig et al., 2014), moral convictions (Nilsson et al., 2016, 2020), or values (e.g., Joireman & Duell, 2007) might play a role in this context. In an unprecedented global crisis such as a pandemic, some people might react with less prosocial behavior (because of fear and anxiety) whereas others could react with more prosocial behavior (because of empathic concern, the perception that one’s have an obligation to help, or that one can “make a difference” for others; Erlandsson et al., 2015). The available data does not allow us to draw conclusions about individual differences, but this is surely an interesting path for future studies. For example, early research on the “Scrooge-effect” suggested that mortality salience increased prosociality only among individuals with who score low on self-transcendental values (Joireman & Duell, 2007).

The data was also aggregated over all charity organizations with a 90-account. Although all these are similar in that they are certified and follow the rules of the Swedish Fundraising Control, they are different in that they focus on different charitable causes and beneficiaries. Prosociality toward ingroup beneficiaries is typically driven by different psychological mechanisms than prosociality toward outgroup beneficiaries (Erlandsson et al., 2019; Nilsson et al., 2020; Politi et al., 2021; Stürmer et al., 2005), and some studies have suggested that mortality salience increases monetary donations toward the ingroup but decreases monetary donations toward outgroups as well as the willingness to sign up for organ donations (Hirschberger et al., 2008; Jonas et al., 2002, 2013). It could thus be the case that organizations devoted to foreign causes (outgroup-charities) obtained relatively less Swedish donations as a result of the pandemic outbreak, whereas organizations that are perceived to help people in Sweden (ingroup-charities) received more donations, but our available Swish data does not allow us to say anything about this.

Still, the abovementioned annual report (GIVA Sverige, 2021) included information about how each charitable organizations in Sweden fared in 2019 and 2020. Although charitable organizations can be classified in different ways, one previously validated classification scheme (Erlandsson et al., 2019) divides Swedish organizations into outgroup-charities, ingroup-charities, and environmentally focused charities. Among the nine outgroup-charities in this classification scheme, five (55.5%) received less money in 2020 than in 2019, and these organizations lost more than 13.9 million SEK in revenue in total. Likewise, three of the four environmentally focused charities (75%) received less money in 2020, and the total loss in revenue for them was around 22 million SEK. In sharp contrast, only two of the nine ingroup-charities (22.2%) received less money in 2020 than in 2019, and the total gain in revenue among these was over 135 million SEK. This evidence is highly anecdotal but might still tentatively suggest that organizations that are perceived to aid Swedish beneficiaries are overrepresented among those who received more donations, while organizations focusing on foreign beneficiaries or on the environment are overrepresented among those who lost revenue as a result of the pandemic. This hypothesis should be tested more rigorously in future studies.

Moreover, it is possible that there are cross-national variations in how the pandemic influenced charitable donations. The current study narrowed its scope to investigate spontaneous monetary donations made by Swish users in Sweden, and this obviously limits generalizability, because the pandemic hit countries around the world in different ways, and whereas Sweden is a welfare state, people are a lot more dependent on the help of others around them, local communities, and religious institutions in many other countries where the social safety nets are weaker (Norenzayan et al., 2013). We did not consider potential effects of the pandemic on “informal” charitable donations (such as giving to street beggars or to charity initiatives without a 90-account). Arguably, direct donations to local organizations such as schools, hospitals and churches make up a much larger proportion of total donations in countries with weaker social safety nets than in Sweden (Varnstad & von Essen, 2013).

Relatedly, we did also not consider other types of helping behavior, such as formal and informal volunteering (such as buying groceries for elderly or donating blood), or on “infection-reducing prosociality” (such as self-isolating and wearing a mask in order to reduce the spread of the virus). In a recent international survey based on self-reports, the percentage of people donating money to charity increased from 28% in 2019 to 31% in 2020 (Charities Aid Foundation, 2021) whereas the percentage of people who volunteered remained stable at 19%. The same survey also showed large differences in both donations and volunteering between different countries (e.g., around 60% reported donating in the United Kingdom and Australia whereas less than 15% reported donating in Portugal and Japan), and prosociality clearly increased in some countries in 2020 (e.g., Indonesia), whereas it clearly decreased in others (e.g., Canada and Ireland). The current study should thus be seen as one piece of the puzzle rather than as a final verdict about how COVID-19 affected human prosociality universally.

4.2 | Managerial implications

The null results of the time series analyses reported in this research suggest that the initial fears reported by charitable organizations
(GIVA Sverige, 2020) were largely unfounded. Although the pandemic caused uncertainty and anxiety both among people working in the charitable sector and among donors, it did not cause people to swish less money to charity. At the same time, because of inherent limitations with quasi-experiments, we cannot say for sure whether this null-effect is because of an absence of any effect of the pandemic or because there were effects in opposite directions that canceled each other out. It could be the case that the pandemic outbreak decreased donations in some ways (e.g., because of added insecurity) but increased it in other ways (e.g., because of a greater mortality salience or even because of people having more available money as a result of less spending on traveling or eating out).

This research provided two additional insights with potential managerial implications. The first is that people swish clearly more money during the weeks when they receive their monthly payment, which suggests that organizations might benefit from launching fundraising campaigns on paydays. The second insight is that the day with the most Swish donations (both in absolute and relative terms) was on April 11, 2020, in the midst of the pandemic. The only plausible reason for this is the televised gala “An evening together,” intended to provide comfort, entertainment, and a sense of unity to Swedish people confined to their homes while raising money to various organizations involved in national helping efforts during the pandemic (Radiohjälpen, 2020). This gala might have been particularly successful because the fundraising cause (the pandemic) was on almost everyone’s mind at the time. Contributing reasons for this are immediacy effects (i.e., increased motivation to support the cause one heard about most recently; Huber et al., 2011) and friends of victim-effects (i.e., increased motivation to support causes that one’s near and dear suffered from; Small & Simonsohn, 2008) on charitable giving. It is possible that organizations that succeed in connecting events and viral news to their charitable work have an advantage compared to those that do not.

4.3 Concluding remarks

Did the COVID-19 pandemic outbreak influence spontaneous charitable donations in Sweden? We investigated this by conducting interrupted time series analyses of weekly amounts donated to charity organizations through Swish in 2019 and 2020. In spite of the quality of the data and the methodological strengths of this approach, the results do not suggest that the pandemic outbreak had any negative or positive overall effect on Swish donations in general, although we observed several seasonal and event-specific fluctuations. Future research should further investigate if some types of charities gained more or less money during the weeks when they receive their monthly payment, which suggests that organizations might benefit from launching fundraising campaigns on paydays. The second insight is that the day with the most Swish donations (both in absolute and relative terms) was on April 11, 2020, in the midst of the pandemic. The only plausible reason for this is the televised gala “An evening together,” intended to provide comfort, entertainment, and a sense of unity to Swedish people confined to their homes while raising money to various organizations involved in national helping efforts during the pandemic (Radiohjälpen, 2020). This gala might have been particularly successful because the fundraising cause (the pandemic) was on almost everyone’s mind at the time. Contributing reasons for this are immediacy effects (i.e., increased motivation to support the cause one heard about most recently; Huber et al., 2011) and friends of victim-effects (i.e., increased motivation to support causes that one’s near and dear suffered from; Small & Simonsohn, 2008) on charitable giving. It is possible that organizations that succeed in connecting events and viral news to their charitable work have an advantage compared to those that do not.

ACKNOWLEDGMENTS

We are very grateful toward GetSwish AB and toward GIVA Sverige for providing data. This work was supported by the Swedish Research Council under Grant number 2017-01827 (Arvid Erlandsson). GetSwish AB, GIVA Sverige and the Swedish Research Council had no role in study design, data analysis, decision to publish, or preparation of the manuscript. Allegra Maguire’s contribution of connecting the authors is gratefully acknowledged.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

ENDNOTES

1 The replicability of mortality salience effects posited by terror management theory is disputed (see Chatard et al., 2020; Klein et al., 2019).

2 We acknowledge that spontaneous donations are increasingly performed on social media, but donating via Swish (233 million SEK in 2020) is still clearly preferred compared to e.g. donating via Facebook in Sweden (89 million SEK; GIVA Sverige, 2021).

3 Only the 20 largest organizations are presented in the report, but we obtained additional data from GIVA Sverige.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from GetSwish. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the author(s) with the permission of GetSwish. The article is based on secondary data that we received from the private company GetSwish AB. The data include no information about the identity of the individuals who sent the payments or about the organizations that received them, and no information about the unique number of donations. Part of the agreement we made to obtain the data was that the raw data would not be shared publicly. Still, in order to be transparent, we will share the data (as well as the R codes) with researchers who want to analyze it in alternative ways.

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**How to cite this article:** Erlandsson, A., Nilsson, A., Ali, P. A., & Västfjäll, D. (2022). Spontaneous charitable donations in Sweden before and after COVID: A natural experiment. *Journal of Philanthropy and Marketing*, e1755. [Online]. Available: https://doi.org/10.1002/nvsm.1755