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Doing well by doing good? Quasi-experimental evidence from corporate philanthropy in banking

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ABSTRACT

This paper asks whether a highly visible corporate-philanthropy campaign raises a bank's market valuation. We study Bank of Chile's two-decade role as official sponsor of the national *Telethon*, using daily share prices for all four listed Chilean banks between 2000 and 2020, spanning sixteen editions of the campaign. We compare Bank of Chile's stock performance around each campaign with that of the other banks, first using share-price levels and then using measures that strip out ordinary market movements, such as daily returns and abnormal returns. Price levels suggest a positive, significant effect, seemingly supporting the idea that doing good pays off financially. This turns out to be an artifact of how stock prices drift over time: once we look at returns instead of levels, the effect disappears entirely, becoming negligible and statistically indistinguishable from zero, consistently across benchmarks, estimation choices, and each edition. We conclude that this sponsorship left no measurable footprint on shareholder value, neither a benefit nor a cost. If such philanthropy creates value, it likely accrues gradually, through customer loyalty and reputation, rather than through daily stock prices. The broader implication is methodological: claims about the financial effects of one-off corporate events should be tested on outcomes that filter out ordinary price trends, not raw price levels, which can manufacture an effect that is not really there. A limitation is that we measure sponsorship visibility rather than the undisclosed monetary value of donations, and that only four banks are listed on the exchange, limiting statistical power.

1. Introduction

Corporate philanthropy (CP) is often justified as a non-market strategy to build reputation, trust, and customer loyalty—factors that are especially valuable in banking. Yet credible evidence on whether high-visibility campaigns translate into measurable financial gains in this sector, particularly in emerging markets, remains scarce. We ask: *Does participation in a prominent philanthropy campaign raise a bank's market valuation, and under what conditions?*

We examine Bank of Chile's participation in the Chilean telethon, *Teletón* in Spanish — a recurrent, nationally televised fundraising event — with a panel of daily stock prices for the four listed banks (Bank of Chile, Santander, BCI, Itaú) over 2000–2020. We implement (i) event-year difference-in-differences (DID) specifications that compare Bank of Chile with the other listed banks before and after each campaign window, and (ii) pooled two-way fixed-effects models that absorb bank and time effects and allow for controls. The identifying variation comes from differential within-year changes around the campaign's start relative to the other

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banks. Because the listed cross-section contains only four banks, we do not rely on clustering along the bank dimension; our preferred inference benchmarks each bank's return against the market index and clusters by date. We assess parallel trends with a treated-versus-comparison event study and report that, in the immediate pre-event window, the treated and comparison banks show no differential trend (no anticipation); given the small cross-section, we treat this as a no-anticipation test rather than a fully powered dynamic design. Throughout, our estimand is the *salience* of official sponsorship rather than the peso value of the bank's donations, which is not separately disclosed, and we keep the causal interpretation correspondingly cautious.

Because the sign of this relationship was genuinely unknown ex ante — no prior study, to our knowledge, observes a single, high-salience campaign repeated over two decades at daily frequency — the evidence is equally informative whether the estimated effect is positive, negative, or null. Our commitment is to identifying the effect correctly, not to a particular direction; and that commitment proves decisive, because the headline answer depends entirely on the stationarity of the outcome. Estimated on price levels, the pooled DID coefficient is positive and apparently significant; but this significance rests on standard errors that ignore the strong serial dependence of a near unit-root series, and the coefficient reverses sign under finer time effects. Once inference accounts for serial correlation and the outcome is made stationary — first differences, returns, and CAPM abnormal returns — the effect vanishes, edition by edition and on average.

Our work connects three strands. (i) Research on CP/CSR and firm value shows potential reputational insurance and performance gains when stakeholder alignment is strong, see for instance Godfrey (2005), Servaes and Tamayo (2013), Flammer (2015), Gautier and Pache (2015), and Choi et al. (2023). (ii) Banking studies highlight the strategic use of philanthropy under competition—donations can support deposit growth and profitability in contested markets, see Choi et al. (2023). (iii) Empirically, rigorous identification in CSR settings often relies on DID or event-style designs with high-dimensional fixed effects. We follow this tradition and implement efficient FE estimation for daily panels.

This paper makes three contributions, the first of which is a cautionary methodological result. *First (methodological)*, we show that a DID applied to stock-price levels — even after normalizing or standardizing them — can yield a spurious "philanthropy effect", significant only under inference that ignores serial dependence and not robust to the granularity of the time effects, because prices are highly persistent. *Second (empirical)*, using first-differenced and CAPM abnormal-return outcomes, we provide what is, to our knowledge, the first daily-frequency, market-benchmarked test of a single, repeated, high-salience philanthropic campaign in an emerging market, and we find no robust valuation effect. *Third (interpretive)*, we show the null is what rational pricing predicts here, because the sponsorship is economically negligible relative to firm value; this reconciles our result with the conditional, often-small giving–value links documented in careful firm-level work (Hogarth et al., 2018; Servaes & Tamayo, 2013).

Section 2 reviews related work and Section 3 the institutional context. Section 4 describes the data and the construction of normalized, standardized, and abnormal-return measures. Section 5 details the identification strategy and event windows. Section 6 reports the level-based estimates, shows why they are not robust, and presents the stationary-outcome results and robustness checks. Section 7 discusses implications for managers and policymakers and outlines avenues for future research.

2. Literature review

We briefly review the empirical literature on corporate philanthropy in banking. The role of corporate philanthropy in enhancing financial performance and competitive positioning has been widely studied, especially in industries where reputation and trust are key. Early research by Brammer and Millington (2005) emphasizes the long-term financial benefits of corporate giving, showing that well-executed philanthropy can enhance firm value. Similarly, Godfrey (2005) demonstrates how corporate philanthropy generates moral capital, offering reputational insurance that mitigates negative reactions during crises.

In banking, corporate philanthropy has been seen as a tool to strengthen customer loyalty and market share. Choi et al. (2023) show that local competition drives banks to increase donations, which boosts deposit market shares and profitability. Their findings align with Wang and Qian (2011), who argue that corporate philanthropy not only secures reputational benefits but also enhances firms' political capital, especially in regulated industries like banking. Expanding this, Servaes and Tamayo (2013) link the effectiveness of CSR initiatives to stakeholder alignment, suggesting that CSR yields greater financial returns when aligned with consumer expectations.

Recent studies have also examined the diminishing returns of philanthropy. Flammer (2015) shows that while moderate CSR efforts improve financial performance, excessive efforts may lead to resource misallocation, supporting the idea that strategic balance is crucial. A recurring theme in the more careful firm-level literature is that the giving–value relationship is conditional and modest rather than automatic: Hogarth et al. (2018) show that the direct relation between corporate giving and firm value is contingent on accompanying reputation management and can even be negative in its absence. This perspective is directly relevant to our findings below.

Methodologically, this paper draws on the long tradition of quasi-experimental evaluation using longitudinal treatment and comparison groups, originating in work such as Ashenfelter and Card (1985) and exemplified by Card and Krueger (1994), as well as on Bertrand et al. (2004), who emphasize the importance of appropriate inference in difference-in-differences (DID) designs. We use DID analysis to study the relationship between philanthropy and financial performance. This approach aligns with studies like Li et al. (2019), who analyze stock price impacts of CSR initiatives using event studies, and Huang and Watson (2015), who use panel data models to control for firm-specific and temporal factors. We add to this methodological tradition a cautionary point that is easy to overlook in daily financial data: difference-in-differences must be estimated on stationary outcomes, since, when applied to highly persistent price levels, the estimator can confound within-period drift with treatment.

Unlike broader CSR literature, which often aggregates various initiatives under one framework, this paper provides a detailed analysis of a single, high-visibility philanthropic event: the Chilean Telethon. This allows for a focused examination of reputation building and financial returns in emerging markets, an area less explored in the literature. While studies like Aguilera et al. (2007) focus on institutional pressures in developed markets, this paper contributes to understanding how such pressures manifest in emerging economies, where cultural and economic factors can influence the effectiveness of philanthropy. This paper contributes to the literature by putting forward empirical findings on the financial impacts of corporate philanthropy using a national campaign case study, and offers new insights into the context-dependent — and, as we show, often negligible — nature of corporate philanthropy's market valuation in emerging markets.

3. The Chilean Telethon: Institutional context

The Chilean Telethon, first held in 1978, has raised over $470 million USD (as of 2021), with participation from private companies, including financial institutions, and millions of Chilean citizens. Created by television personality Mario Kreutzberger ("Don Francisco"), it was inspired by similar events abroad to help children with motor disabilities.

The Telethon is organized by the Telethon Foundation, a private non-profit that runs 14 rehabilitation centers across Chile. These centers provide physical therapy, medical care, psychological support, and educational services to children with disabilities, focusing on promoting their social inclusion and independence. The foundation's bi-annual budget relies heavily on donations raised during the event, highlighting the importance of corporate and individual contributions for its sustainability. Over the years, the Telethon has become a significant social and financial event, contributing to major advancements in rehabilitation services.

Corporations contribute 40%–60% of total donations, emphasizing the vital role of private-sector partnerships. The Telethon also represents a shift in philanthropy in Chile, where such initiatives traditionally relied on private foundations and religious institutions.

As a national media event, the Telethon is broadcast by over 20 television channels and covered extensively by newspapers and online platforms. This widespread media coverage allows companies to use the event for both philanthropic purposes and brand promotion, helping them improve their public image and strengthen their social responsibility credentials. We interpret Bank of Chile's philanthropy effort as its role as official sponsor of the Chilean Telethon, and operationalize it as a binary indicator of official, high-salience sponsorship, aligning with the assumption that philanthropy influences reputation through visible channels.

3.1. The role of the banking sector in the Telethon

Founded in 1893, Bank of Chile is one of the country's oldest financial institutions, holding 20.4% of the loan market and 22.3% of the deposit market as of 2023. It is publicly traded, with majority ownership by Quiñenco Group, part of the Luksic family, one of Chile's wealthiest conglomerates. Bank of Chile has played a key role in Chile's financial development, including helping the country recover from crises like the Latin American debt crisis in the 1980s and the global financial crisis in 2008.

In addition to its financial leadership, Bank of Chile is a major player in philanthropy, particularly through its long-standing partnership with the Chilean Telethon. Since the Telethon's inception, Bank of Chile has been its official banking partner and operational collection platform: it hosts the campaign's official donation account, through which the funds raised are channeled and jointly reported with the Foundation, and mobilizes thousands of employee volunteers each edition (Fundación Teletón, 2024). With over 300 branches across Chile, the bank is a key donation point; during the Telethon it extends branch hours and many employees volunteer to help collect donations. This logistical support is crucial, as physical donations make up a large portion of the funds raised.

Bank of Chile's involvement also highlights how corporations, especially banks, use philanthropy as a strategic tool. Participation in the Telethon enhances the bank's corporate image and reputation, helping to build customer loyalty and brand trust. In this case, philanthropy serves not only as a charitable act but also as a strategic investment in customer relations.

In the broader context of Corporate Philanthropy (CP), Chile's banking sector has moved from financial intermediation to active participation in social causes. Bank of Chile is a leader in integrating CP into its strategy, supporting initiatives in education, health, and community development. The Telethon is a key example of how banks can leverage their resources to support national efforts. Bank of Chile's continuous involvement in the event aligns with its broader CP agenda, focusing on community engagement and corporate citizenship.

Beyond collecting donations, Bank of Chile also directly contributes funds and operates the financial infrastructure that ensures the smooth transfer of funds to the Telethon Foundation. Its role as the *official*, co-branded banking sponsor — featured prominently in the national broadcast — is qualitatively distinct from the involvement of the other listed banks, which have, at most, lower-visibility or incidental exposure (for example, enabling electronic transfers into the official account). This distinction defines our treatment, and — as explained in Section 5 — our headline specification benchmarks each bank against the market index rather than against the other banks, so the analysis does not require the comparison banks to be entirely free of any philanthropic activity.

Table 1
Market share of banks and HHI.
Source: Self-made with data from the Chilean Financial Market Commission.

Banks	Branches	Assets	Cash	Equity	Cont. Cred.
Banco Bice	1.7%	2.9%	4.7%	2.9%	2.3%
Banco BTG Pactual Chile	0.1%	0.9%	2.0%	1.8%	0.5%
Banco Consorcio	1.2%	2.1%	2.3%	2.2%	0.3%
Bank of Chile	18.1%	13.6%	13.5%	16.5%	18.9%
Banco de Credito e Inversiones	13.8%	19.7%	18.5%	17.2%	18.9%
Banco del Estado de Chile	27.9%	14.8%	23.0%	10.8%	9.1%
Banco Falabella	5.0%	1.7%	2.1%	3.4%	4.8%
Banco Internacional	0.8%	1.1%	1.2%	1.0%	0.6%
Banco Itaú Chile	7.8%	10.6%	8.9%	12.1%	12.1%
Banco Ripley	0.9%	0.3%	0.2%	0.7%	1.8%
Banco Santander-Chile	13.5%	17.3%	9.0%	14.5%	17.2%
Banco Security	1.3%	2.7%	2.3%	2.8%	2.1%
Bank of China	0.1%	0.0%	0.2%	0.3%	0.0%
China Construction Bank	0.1%	0.1%	0.4%	0.4%	0.1%
Hsbc Bank (Chile)	0.1%	0.4%	1.1%	0.4%	0.1%
Jp Morgan Chase Bank, N.A.	0.1%	0.3%	2.3%	1.4%	0.1%
Scotiabank Chile	7.6%	11.5%	8.4%	11.6%	11.2%
HHI	1631	1361	1334	1216	1404

Note: *Assets* is the total assets of the bank; *Cash* is "Cash and bank deposits" (a fraction of the total assets); *Equity* is total equity of the bank; *Cont. Cred.* is contingent credits of the bank. *HHI* is the Herfindahl–Hirschman Index, which represents market concentration.

3.2. Chilean banking sector

There are four main banks in Chile: Banco del Estado de Chile,[1] Bank of Chile, Banco Santander (Chile), and Banco de Crédito e Inversiones (BCI). Together, they account for 73.3% of all bank branches in the country. In terms of total assets, they hold 65.4%, and in cash and bank deposits, this figure is 64.1%. Their total equity market share is 59%, and for sovereign credits, it is 64.2%. Following these banks are Banco Itaú and Scotiabank, which each have around a 10% market share. The Herfindahl–Hirschman index for market concentration averages 1389, indicating a moderately concentrated market (see Table 1).

Bank of Chile has been the official banking sponsor of all versions of the Telethon. For this study, we compare the evolution of Bank of Chile's share price with those of Santander, BCI, and Itaú, chosen based on their market share. BancoEstado and Scotiabank were not included because they do not have data available on the Santiago Stock Exchange.

4. Data

4.1. Data sources

To explore how prices change in the banking industry, we use data from the Santiago Stock Exchange, accessible via its website.[2] The Stock Exchange provides stock market data for Chilean and international firms, including share prices, traded volumes, and fixed income instruments. Public access is limited to the last month's events, while private access allows downloading historical data for over 25 years, updated every 31 days. For this study, a database was created with information from Chilean banks listed on the stock market: Bank of Chile, Banco Santander, Banco de Crédito e Inversiones (BCI), and Banco Itaú. Bank of Chile is the official sponsor of all versions of the *Telethon*, a role the other banks do not hold.

Some variables, such as stock condition (T, C, or V), ISIN code, and certain price metrics (major, minor, average, opening), were not relevant and were removed. The final database consists of panel data for the banks, including time, date, price, price-to-earnings ratio, price-to-book ratio, and the company name, as shown in Table 2.

The database for this study contains 19,979 observations: 5175 from Bank of Chile, 5095 from Banco de Crédito e Inversiones (BCI), 5223 from Banco Santander, and 4486 from Banco Itaú. The difference in observations between Banco Itaú and the other three banks is because the former has data available only since November 2002, while the others have data starting from January 1, 2000. Bank of Chile, the official banking sponsor of the Telethon since its inception, is the treated unit; the other three banks (Santander, BCI, and Itaú) — which have, at most, lower-visibility or incidental exposure — serve as the comparison group. We study the sixteen editions of the *Teletón* held over our sample window.[3]

[1] Better known as *BancoEstado*, it is the only public commercial bank in Chile.

[2] https://www.bolsadesantiago.com/

[3] The editions studied are those of 2000, 2002, 2003, 2004, 2006, 2007, 2008, 2010, 2011, 2012, 2014, 2015, 2016, 2017, 2018, and 2020—sixteen in total. The edition scheduled for 2019 was postponed to April 2020 because of the social unrest of late 2019, and enters the analysis as the 2020 edition; the campaign is generally not held in years with national elections.

Table 2
Description of variables.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange.

Original variable	Translation	Meaning
Fecha	Date	Daily date
Precio	Price	Average price that stocks reach within the day
Ratio precio/utilidad	Price-to-earnings ratio	Share price/earnings per share
Razón bolsa/libro	Price-to-book value	Share price/book value
Razón social	Business name	Self-explained

Table 3
Descriptive statistics.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange.

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
Treatment						
Price (CLP)	5175	55.684	60.4	25.16	16.8	105.5
Ratio P/U	5175	13.924	14.27	4.547	0	31.75
Ratio P/B (wins.)	5116	3.115	3.09	0.645	0.33	5.09
Equity (tn CLP)	5175	4.84	4.81	2.89	0.922	10.7
Control						
Price (CLP)	14 804	7796.47	31.69	12 970.51	1.805	47 500
Ratio P/U	14 804	17.346	13.75	51.847	0	999.99
Ratio P/B	14 804	2.399	2.33	0.92	0.28	6.5
Equity (tn CLP)	14 804	3.227	2.85	2.395	0.3264	10.41

Note: *Price* is in Chilean pesos (CLP), and *Equity* is in trillions of Chilean pesos. Bank of Chile's P/B is winsorized to remove 59 extreme outliers (see text).

4.2. Descriptive statistics

Table 3 shows the descriptive statistics for the variables of interest (price, price-to-earnings ratio, price/book ratio, and stockholders' equity) over the study period (2000–2020). Our empirical implementation uses the stock price as a proxy for financial performance. Stock prices reflect market expectations for both assets and liabilities, making them suitable for testing the overall predictions. Future research with disaggregated data on loans and deposits could better validate the structural predictions.

The mean, minimum, maximum values, and standard deviation for the *Price* variable differ significantly. For Bank of Chile, the price is in the tens, while for the other banks, it is in the thousands. For the treatment group (Bank of Chile), the mean and median prices are \$55.7 and \$60.4, respectively. In the control group, the mean is \$7796.5, and the median is \$31.7. The large difference between the mean and median in the control group is mainly due to BCI's share price, which is much higher than the other banks. Since the share prices of the banks differ greatly, they were normalized and standardized to allow for comparisons. We flag one data-quality issue and treat it consistently throughout: Bank of Chile's price-to-book series contains 59 extreme outliers (values up to 238, versus a sensible maximum near 5), which we winsorize consistently across all descriptive statistics and regressions; results are unchanged whether the outliers are winsorized or dropped.

$$\text{Normalized Price} = \frac{\text{Price} - \text{Price}_{\min}}{\text{Price}_{\max} - \text{Price}_{\min}}, \qquad \text{Standardized Price} = \frac{\text{Price} - \mu}{\sigma}.$$

Where $\text{Price}_{\min}$ is the minimum price of the series, $\text{Price}_{\max}$ the maximum, μ the mean, and σ the standard deviation. The *Normalized Price* ranges between 0 and 1, allowing direct comparison of share prices across firms and over time; the *Standardized Price* has mean 0 and standard deviation 1. Table 4 reports the descriptive statistics for both variables. We also create the treatment indicator (*Treatment* = 1 for Bank of Chile, the official sponsor), the period indicator (*Post* = 1 during a campaign window), and their interaction (*DID*).

Calculating the Pearson correlation coefficient reveals a high positive relationship between the price series from 2000–2020, with values in the range $[0.96, 0.99]$, except for Banco Itaú, whose correlations with the other banks are around 0.75 for the 2003–2020 period (see panel 1 of Table 5). Panel 2 shows the correlations for the price-to-book ratio, ranging over $[0.59, 0.83]$. These high comovements — consistent with a single dominant market factor — motivate the market-model benchmark we adopt below.

4.3. Stationary outcome variables

Because daily prices (and any monotone rescaling of them) are highly persistent, we complement the level measures with stationary outcomes that are the basis for our inference. We compute the daily log return $r_{it} = \ln(P_{it}/P_{i,t-1})$; the first differences of the normalized and standardized series; and the CAPM abnormal return $AR_{it} = r_{it} - (\hat{a}_i + \hat{b}_i R_{mt})$, where R_{mt} is the daily return on the market index. We use the IGPA as the main benchmark and the IPSA as a robustness check, and estimate $(\hat{a}_i, \hat{b}_i)$ both over the full sample and on rolling (prior-250-day, lagged-30-day) windows.

Table 4
Descriptive Statistics of new variables.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange.

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
Treatment						
Norm. Price	5175	0.438	0.492	0.284	0	1
Std. Price	5175	0	0.188	1	−1.546	1.98
Control						
Norm. Price	14 804	0.426	0.465	0.265	0	1
Std. Price	14 804	0.002	0.149	0.999	−1.646	2.31

Note: Within each group the mean and standard deviation of the standardized price equal 0 and 1; the pooled control figures differ slightly because the control group contains three banks.

Table 5
Correlations.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange.

Bank	Chile	BCI	Itaú	Santander	Chile	BCI	Itaú	Santander
(1) Chile	1.000				1.000			
(2) BCI	0.990	1.000			0.768	1.000		
(3) Itaú	0.749	0.765	1.000		0.588	0.694	1.000	
(4) Santander	0.958	0.964	0.721	1.000	0.638	0.830	0.609	1.000

Note: First panel shows correlations between banks' share prices; second panel shows correlations between the Price-to-Book ratio.

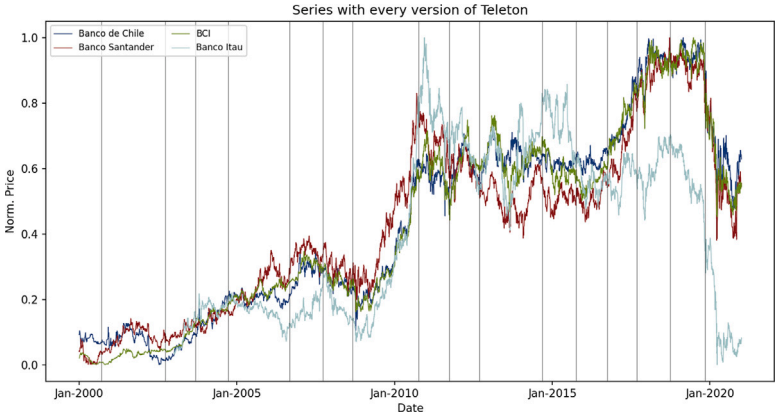


Fig. 1. Time series of normalized share prices for every version of the Telethon.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange.

5. Empirical methodology

5.1. Identification strategy

The *Telethon* is an annual fundraising campaign[4] to support people with disabilities undergoing rehabilitation. It usually takes place during the last weekend of November or the first weekend of December,[5] starting on Friday night and ending around midnight on Sunday. For 2000–2004, campaign advertising start dates are proxied by the modal start day from later editions; robustness shifts the start ±7 and ±14 days and re-estimates all windows.

In econometric terms, Bank of Chile is the official, high-salience banking sponsor and operational collection platform for the campaign, a role it has held in every edition; the comparison banks have, at most, lower-visibility or incidental exposure. The design contrasts the behavior of Bank of Chile's price around each campaign with that of the comparison banks, before and after the campaign window. Fig. 1 shows the time series of normalized prices, with vertical bars indicating the start of the *Telethon* campaign.

Fig. 2 shows the time series of current share prices for each bank. Bank of Chile, Banco Santander, and BCI have similar price trends, while Banco Itaú shows a slightly different behavior.

[4] The *Telethon* is not held in some years, typically during Chile's political elections.

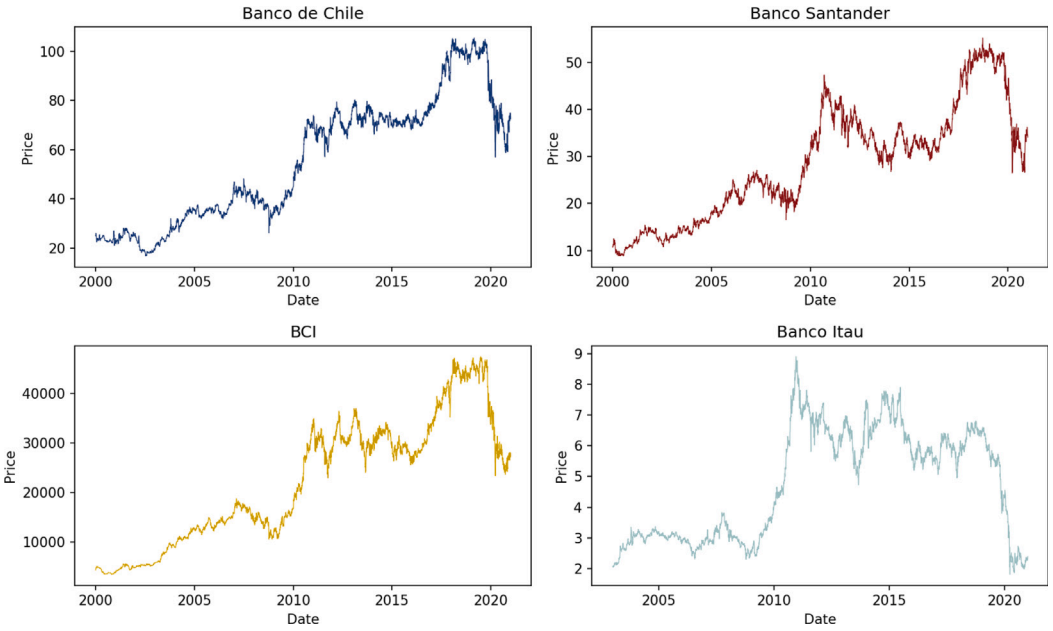


Fig. 2. Time series of share prices.
Source: Self-made with data from the Santiago Stock Exchange.

To answer the research question, a difference-in-difference (DID) analysis was performed using two dependent variables, *Normalized Price* and *Standardized Price*, comparing Bank of Chile with the comparison banks before and after each event. The general DID model is:

$$P_{it} = \beta_0 + \gamma\, Treatment_i + \lambda\, Post_t + \delta\, D_{it} + \epsilon_{it}, \tag{1}$$

where $i = 1, \ldots, 4$ indexes the institution and t the period; $Treatment_i$ equals 1 for Bank of Chile (the official sponsor) and $Post_t$ equals 1 in the post-treatment period. D_{it} (the *DID* term) is the interaction of $Post$ and $Treatment$; under strict exogeneity the DID estimator δ captures the effect of the campaign. As we explain in Section 6, when P_{it} is a price level this specification is unreliable, and our preferred outcome is therefore the CAPM abnormal return.

5.2. Parallel trends

Fig. 3 shows the time series of *Normalized Prices* for each bank; Bank of Chile, Banco Santander, and BCI follow a similar trend, while Banco Itaú differs somewhat. Fig. 4 presents the same with *Standardized Prices*. These comovements can be compared with the correlation coefficients in Table 5. A more formal assessment of parallel trends — a flat pre-event path of cumulative abnormal returns — is reported with the event study in Section 6.5, and supports the identifying assumption within our windows.

5.3. From price levels to stationary outcomes

The DID estimator in Eq. (1) is valid only if its outcome is stationary. Daily bank prices are not: they are highly persistent, near unit-root series. Applied to such a series, the interaction δ absorbs any within-window drift in the treated bank's price relative to the comparison banks, whether or not that drift has anything to do with the campaign. We therefore report the level-based estimates (Section 6.1) as a diagnostic, show that they are not robust (Section 6.3), and base our conclusions on three stationary specifications: (i) a returns DID, $r_{it} = \alpha_i + \tau_t + \delta\, DID_{it} + X'_{it}\beta + \varepsilon_{it}$, with bank and calendar-day fixed effects; (ii) the same DID on CAPM abnormal returns AR_{it} (our headline); and (iii) a market-model event study that cumulates AR_{it} for Bank of Chile over windows around each broadcast (estimation window $[-250, -30]$ trading days), testing cumulative average abnormal returns (CAARs) across editions with a cross-sectional t. Because the cross-section has only four banks, clustering on the bank dimension is unreliable; benchmarking against the market index is our basis for inference.

The dimension along which we cluster is matched to the kind of dependence present in each outcome, and we make this explicit to avoid the impression that the clustering choice varies arbitrarily across tables. Price *levels* are dominated by *serial* dependence

[5] In 2020, the *Telethon* was held in April due to the 2019 Chilean social unrest.

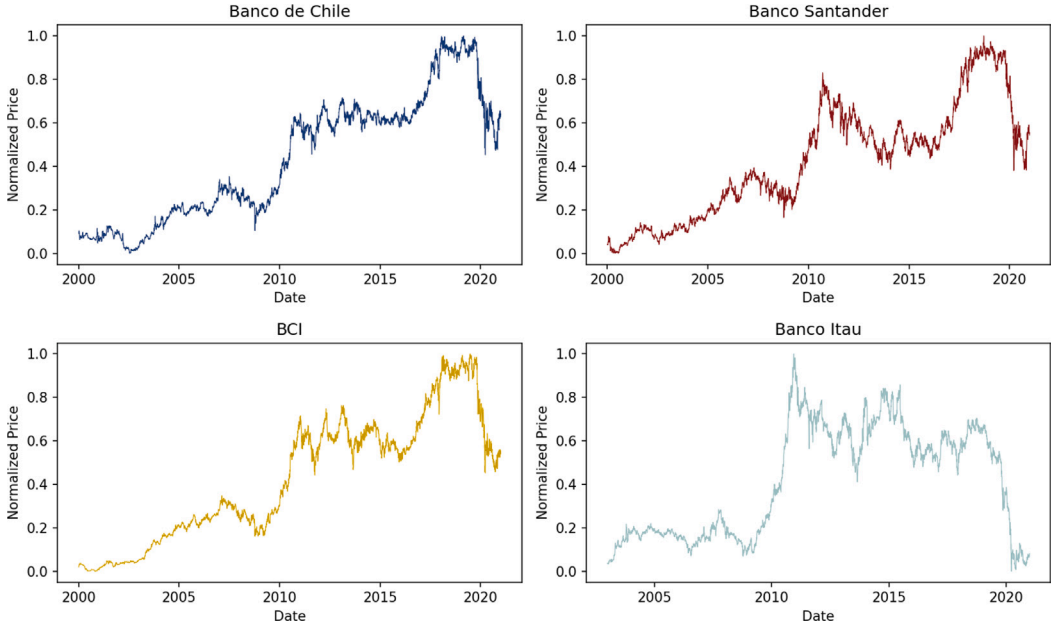


Fig. 3. Time series of normalized share prices.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange.

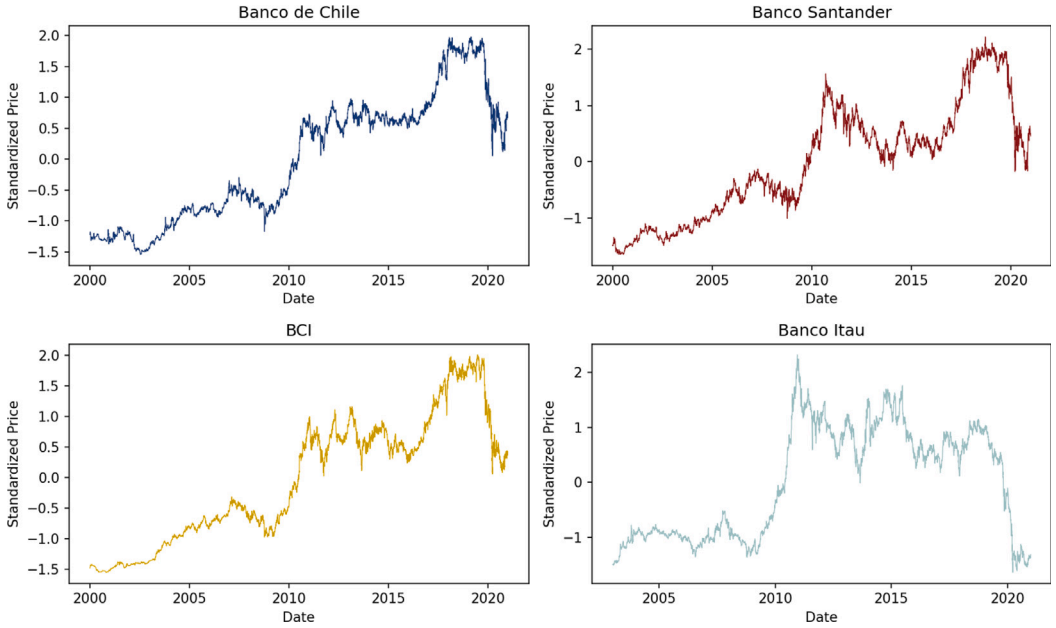


Fig. 4. Time series of standardized share prices.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange.

— each bank's price is highly autocorrelated over time — so the appropriate correction is to cluster by *year*; this is exactly what collapses the apparent significance of the level-DID (Section 6.3), whereas clustering by date, which only addresses same-day cross-bank correlation, does not. Returns and abnormal returns, by contrast, exhibit little serial dependence once differenced; their salient residual dependence is *contemporaneous* (the four banks comove on a given day), which we absorb through calendar-day fixed effects

Table 6
Multiple Fixed Effect Regression (pooled, price levels).
Source: Own elaboration based on data obtained from the Santiago Stock Exchange. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.0138***	0.0144***	0.00980***	0.0457***	0.0486***	0.0312***
	(0.00301)	(0.00300)	(0.00330)	(0.0107)	(0.0107)	(0.0119)
Date			3.83e−05***			0.000145***
			(7.35e−06)			(2.77e−05)
Ratio P/B		0.000169***	0.000168***		0.000830***	0.000826***
		(2.24e−05)	(2.27e−05)		(8.39e−05)	(8.50e−05)
Volume		−3.32e−12	−3.38e−12		−1.11e−11	−1.14e−11
		(3.61e−12)	(3.60e−12)		(1.26e−11)	(1.25e−11)
Constant	0.429***	0.428***	−0.283**	−0.000163	−0.00186	−2.702***
	(0.000670)	(0.000742)	(0.137)	(0.00252)	(0.00274)	(0.515)
Observations	19,979	19,979	19,979	19,979	19,979	19,979
R-squared	0.8799	0.8800	0.8802	0.8755	0.8757	0.8759

Note: Robust standard errors in parentheses. Models (1)–(3) use normalized prices; (4)–(6) standardized prices. High R^2 reflects the inclusion of bank and time fixed effects.

and guard against by clustering on the *date*. The change of clustering dimension across tables is therefore a deliberate matching of the correction to the type of dependence, not an inconsistency.

6. Results

6.1. Estimation using sample splitting

The first analysis treats each *Teletón* as an independent event, using *sample splitting*. Model (1) is run for each of the sixteen editions in 2000–2020. The treatment period is measured from the start of the respective *Teletón* advertising campaign, typically in September; starting in 2006 all campaigns began in September, except 2010 and 2015 (October 5 and 1). For 2000–2004 the exact start date was unavailable, so the average start date of the available editions was used, with adjustments to avoid national holidays. The pre-treatment period is set to the same duration as the treatment period. We complement the DID regressions with a treated-versus-comparison event study (Section 6.5), whose immediate pre-event coefficients show no differential trend between the treated and comparison banks (no anticipation).

We estimate model (1) edition by edition on both the normalized and the standardized price, with and without controls (the price-to-book ratio, a linear time trend, and trading volume). Following the reviewers' suggestion to streamline the empirical exhibits, the full set of per-edition estimates — the original eight tables — is collected in Appendix A (Tables A.1–A.8); we summarize the pattern here. Read at face value, the *DID* coefficient is positive and significant in several editions (2002, 2003, 2006, 2011, 2012, 2015, 2017), negative and significant in a few (2000, 2007), and insignificant in the rest, with the same qualitative pattern for the standardized price and after adding controls. Taken literally, the larger coefficients would imply sizeable price responses—for example, the 2017 normalized-price estimate corresponds to about 12%. The original analysis read this dispersion across editions as evidence of "context dependence". Section 6.3 shows that, once the outcome is made stationary, this dispersion is statistically indistinguishable from noise; we retain the tables in full (in the appendix) for transparency and replicability, because diagnosing them is part of our contribution.

6.2. Two-way fixed effects estimation results

Pooling all editions, we run the model with fixed effects at both the firm and year level:

$$P_{it} = \beta_0 + \sum_{i=1}^{I} \gamma_i \, Treatment_i + \sum_{t=1}^{T} \lambda_t \, Post_t + \delta \, DID_{it} + \epsilon_{it}, \tag{2}$$

estimated with the high-dimensional fixed-effects method of Correia (2016). Table 6 reports the results; models (1)–(3) use normalized prices and (4)–(6) use standardized prices. In all specifications the *DID* coefficient is positive and — under conventional robust standard errors — significant, +0.0138 in the baseline normalized model and +0.0457 in the standardized model, apparently robust to the price-to-book ratio, trading volume, and a time trend. As the note to the table indicates, the high R^2 (above 0.87) reflects the bank and time fixed effects and should not be read as participation explaining the variation in prices; identification rests on δ alone. It is this pooled, positive, seemingly robust coefficient that an analysis confined to price levels would report as the headline evidence for "doing well by doing good". The next subsection shows why that reading does not survive scrutiny.

Table 7
The level-DID coefficient is not robust to inference or to time-effect granularity.

Specification	DID coefficient	*p*-value
Panel A. Normalized price, bank + annual FE; varying standard errors		
Robust (HC), no clustering *(as originally reported)*	+0.0138	0.000
Clustered by date (contemporaneous dependence)	+0.0138	0.000
Clustered by year (serial dependence)	+0.0138	0.449
Panel B. Normalized price, clustered by year; varying time FE		
Annual time FE	+0.0138	0.449
Monthly time FE	−0.0016	0.862
Daily time FE	−0.0010	0.913

The coefficient is "significant" only when inference ignores serial dependence, and it switches sign under finer time effects—hallmarks of a regression on a non-stationary series.

Table 8
First-difference and returns DID: no significant effect.

Dependent variable	DID coefficient	*p*-value
Daily return r_{it}	+0.00065	0.23
Δ Normalized price	+0.00018	0.65
Δ Standardized price	+0.00077	0.59

Two-way (bank, calendar-day) fixed effects; standard errors clustered by date.

Table 9
CAPM difference-in-differences: abnormal return on Teletón participation.

	Pooled	Two-way FE	+ Controls	IPSA benchmark
DID (bps/day)	+6.01	+6.02	+6.27	+5.80
p-value	0.295	0.297	0.278	0.315
Editions significant at 5%			0 of 16	
Editions with positive sign			9 of 16	

Dependent variable: CAPM abnormal return (IGPA market model unless noted). Controls: P/B and volume. Standard errors clustered by date. None significant at conventional levels. The result is unchanged under rolling-window beta estimation.

6.3. Why the level-based estimates are not robust

The positive level-DID coefficient cannot be read as evidence of a philanthropy effect, for two related reasons that Table 7 makes explicit. The table fixes the pooled specification (normalized price; bank and annual fixed effects) and varies only the inference and the granularity of the time effects. First, the +0.0138 coefficient is "significant" under heteroskedasticity-robust errors that treat each bank-day as independent, but is far from significant once errors are clustered by year to reflect the strong serial dependence of a near unit-root series ($p = 0.45$). Clustering by date instead leaves the coefficient significant ($p < 0.01$, Panel A), which is itself diagnostic: it shows that the inference problem is *serial* dependence over time, not *contemporaneous* dependence across the four banks—and it is why our stationary-return specifications, which are not serially dependent in the same way, cluster by date instead (Section 5.3). Second, holding inference fixed, the coefficient is +0.0138 under annual time effects but *changes sign* under monthly or daily effects. A coefficient that is significant only under inference that ignores serial correlation, and whose sign depends on the granularity of the time controls, is not identifying an event response; it reflects within-period drift in a persistent series. We therefore treat the level estimates in Table 6 and Appendix A as a diagnostic of this artifact and turn to stationary outcomes.

6.4. Stationary outcomes: no robust effect

Re-estimating the DID on stationary outcomes eliminates the result. Table 8 reports daily returns and first differences of the normalized and standardized series; none is significant. The CAPM abnormal-return DID (Table 9) is about +6 basis points per day and statistically insignificant throughout: pooled, two-way fixed effects, with controls, and under both the IGPA and IPSA benchmarks ($p \approx 0.28$–0.32). Estimated edition by edition, *none* of the sixteen campaigns is significant at the 5% level (nine of sixteen positive, with point estimates scattered between roughly −21 and +35 basis points). The dispersion across editions that the level specification interpreted as "context dependence" is, on stationary outcomes, indistinguishable from noise.

6.5. Event study and parallel trends

Table 11 and Fig. 5 report market-model CAARs for Bank of Chile around the broadcast. The pre-event window $[-5, -1]$ is a small, insignificant +0.30% ($t = 0.59$), indicating no information leakage in the days before the event. No post-event window is significant; point estimates are economically small and, if anything, slightly negative, and the cumulative path stays within its confidence band throughout.

Table 10
Treated-minus-comparison differential CAAR (dynamic DID) around the broadcast.

Window	Differential CAAR (Bank of Chile – comparison avg.)	t-statistic
Pre-event (parallel-trends/no-anticipation)		
$[-20,-1]$	+3.72%	+2.43
$[-20,-1]$, excl. 2020 (COVID)	+2.54%	+2.44
$[-10,-1]$	+0.62%	+1.12
$[-5,-1]$	+0.13%	+0.26
Event and post-event		
$[-1,1]$	−0.16%	−0.35
$[0,5]$	−0.57%	−0.59
$[0,10]$	−1.49%	−0.84
$[0,20]$	−1.15%	−0.52

Differential of Bank of Chile's CAPM abnormal return minus the average of the three comparison banks (IGPA market model, estimation window $[-250,-30]$), cumulated by event window and averaged across the sixteen editions; cross-sectional t. The immediate pre-event windows show no differential trend; the longer $[-20,-1]$ window shows a modest positive drift that is robust to excluding the 2020 edition. No event or post-event window is significant.

Table 11
Market-model CAARs around the Teletón broadcast (16 editions, Bank of Chile).

Window	CAAR	t-statistic
$[-5,-1]$ (pre)	+0.30%	+0.59
$[-1,1]$	−0.19%	−0.59
$[0,5]$	−0.82%	−0.88
$[0,10]$	−2.06%	−1.22
$[0,20]$	−1.87%	−0.81

IGPA market model, estimation window $[-250,-30]$. Cross-sectional t across editions. No window is significant at conventional levels.

The Bank-of-Chile CAAR in Table 11 shows only that the treated bank's own abnormal returns are flat around the broadcast; it does not, by itself, establish that the treated and comparison banks share a common trend, which is the assumption a difference-in-differences requires. We therefore assess parallel trends directly. Fig. 6 plots the cumulative abnormal return of Bank of Chile against the average of the three comparison banks over an extended $[-20,+20]$ window, and Table 10 reports the treated-minus-comparison differential — a dynamic difference-in-differences — by window. In the immediate pre-event window the two series are statistically indistinguishable: the differential is +0.13% over $[-5,-1]$ ($t = 0.26$) and +0.62% over $[-10,-1]$ ($t = 1.12$), indicating no anticipation. Over the longer $[-20,-1]$ horizon a modest positive differential drift emerges (+3.7%, $t = 2.4$), which is robust to excluding the COVID-affected 2020 edition (+2.5%, $t = 2.4$). We report this transparently. Given only four listed banks, we do not claim a fully powered dynamic difference-in-differences, and we read the immediate-window result as a no-anticipation test, with the market-model benchmark — which differences out common shocks — as the primary safeguard. Importantly, the pre-event drift is *positive*, whereas every post-event window is small and insignificant and, if anything, slightly negative (−0.16% over $[-1,1]$; −1.15% over $[0,20]$). A positive pre-trend biases toward *finding* a positive philanthropy effect, so its presence makes the null we report more conservative, not less credible: had sponsorship generated a genuine value premium, the run-up would have reinforced rather than masked it, yet no post-event premium appears.

6.6. Why the null, magnitudes, and robustness

The null is informative rather than merely imprecise. The pooled daily DID is +6 bps with a standard error near 6 bps, so the design rules out daily effects much beyond ±12 bps—of order ±2% cumulated over a three-week window. By contrast, the mechanical footprint of a sponsor's contribution is at most a few tens of basis points of market capitalization. A single recent edition of the campaign raised on the order of CLP 40–50 billion in total, of which roughly a third came from all corporate donors combined (Fundación Teletón, 2024). Even attributing that *entire* corporate contribution — about CLP 13 billion — to Bank of Chile alone, a gross overstatement given the many participating firms, would amount to only about 0.3% of the bank's median market capitalization (CLP 4.8 trillion, range CLP 0.9–10.7 trillion over the sample); the bank's own direct outlay is a small fraction of that. Against abnormal-return volatility near 110 basis points per day, a footprint of at most a few tens of basis points — and realistically only a few — is one to two orders of magnitude below what a daily event study can resolve. Any economically meaningful valuation effect would therefore have been visible; none was. A null is what rational pricing predicts when the dollar stakes are negligible relative to firm value, and we read our estimate accordingly—as evidence on the salience of official sponsorship rather than on the returns to a measured quantity of giving.

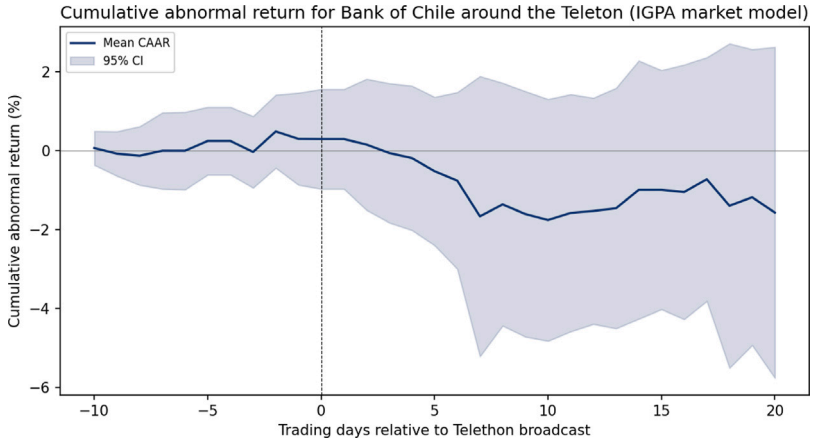


Fig. 5. Cumulative abnormal return for Bank of Chile around the Teletón (IGPA market model). Mean CAAR with 95% confidence band, averaged over sixteen editions.

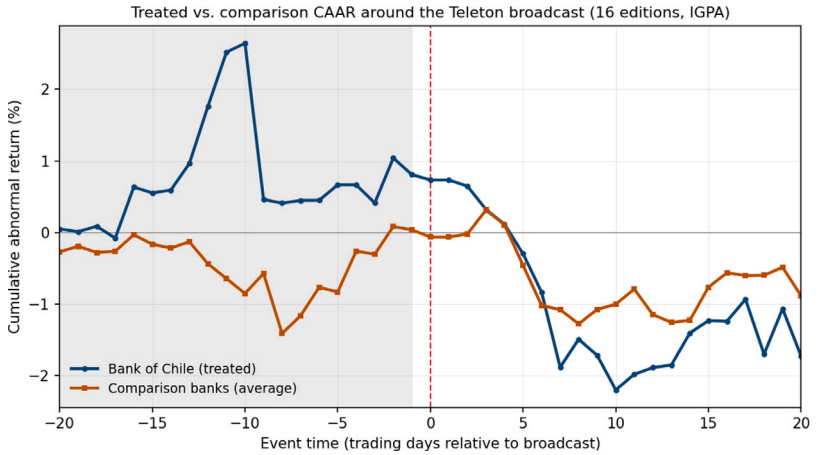


Fig. 6. Treated versus comparison cumulative abnormal returns around the Teletón broadcast. Bank of Chile (treated) and the average of the three comparison banks (BCI, Itaú, Santander), IGPA market model, event time in trading days ($\tau = 0$ is the broadcast), averaged over the sixteen editions. The shaded region is the pre-event window. The two paths track closely through the event; the treated series drifts slightly below afterward, consistent with the null.

The null is stable across: (a) both market benchmarks (IGPA, IPSA); (b) full-sample and rolling-window betas, which removes any concern that full-sample betas absorb the event periods; (c) dropping the 2000–2004 editions, whose advertising-start dates are approximated; and (d) excluding editions that coincide with major bank merger and acquisition activity — Bank of Chile's absorption of Citibank Chile (2008), BCI's acquisition of City National Bank of Florida (2015), and the Itaú–CorpBanca merger (2016) — following Lozada et al. (2021). These confounded editions are among those that produced anomalous signs under the discredited level specification, reinforcing the interpretation that the original cross-edition "heterogeneity" reflected confounds and noise rather than a philanthropy channel. A treated-minus-comparison single-benchmark comparison yields the same small, insignificant difference. We note also that market-wide announcement effects of the kind documented by Stehlík et al. (2023) for the Chilean indices affect a bank and its benchmark symmetrically, and are differenced out by the abnormal-return design. The full set of these robustness estimates — the per-edition abnormal-return effects and the pooled variants (alternative benchmark, beta estimation, event-window timing, sample exclusions, and single-comparison-bank contrasts) — is reported with coefficients and p-values in Appendix B (Tables B.1 and B.2); the effect is small and insignificant throughout.

7. Concluding remarks

This paper asked whether a highly visible philanthropy campaign can measurably raise a bank's market valuation, and under what conditions. Using daily data for the four listed Chilean banks (2000–2020), we studied Bank of Chile's role as official sponsor of the national *Teletón* through event-year difference-in-differences (DID) designs and pooled two-way fixed effects.

Three facts emerge. *First*, a DID applied to persistent price levels — normalized or standardized — produces a positive, apparently significant average coefficient and a mixed pattern of edition-level signs; but this result is an artifact of non-stationarity. Its significance vanishes once standard errors account for serial dependence, and its sign reverses under finer time effects. *Second*, re-estimated on stationary outcomes — first differences, daily returns, and CAPM abnormal returns, across the IGPA and IPSA benchmarks, full-sample and rolling betas, and edition by edition — the sponsor's response is small, positive, and statistically indistinguishable from zero, and the event-study cumulative abnormal returns are flat with no significant window. *Third*, this null is what theory predicts given magnitudes: the sponsorship is a basis-point event relative to market capitalization, so neither its cost nor any plausible reputational benefit of comparable order is detectable in daily prices.

The substantive message is therefore not that "philanthropy destroys value", nor that it confirms "doing well by doing good", but that high-salience philanthropic *sponsorship* leaves no measurable shareholder-value footprint in this setting—neither a premium nor a penalty. This contribution does not depend on the sign of the estimate: a transparent, market-benchmarked null for a prominent, repeated emerging-market campaign is itself informative, and it carries a concrete methodological caution—event-style claims about corporate philanthropy and shareholder value should be estimated on stationary outcomes, not price levels.

The main implications for managers and boards follow from the magnitudes. A salient national campaign is best understood as a reputational and stakeholder investment whose payoff, if any, accrues through slow-moving channels — customer loyalty, deposits, employee engagement — rather than through an identifiable jump in the daily share price. Our results therefore caution against justifying (or evaluating) campaign-level giving by its effect on the stock price: (i) *timing and macro sensitivity* are second-order for valuation precisely because the direct stakes are small; (ii) *salience and execution* matter for reputation, but reputational returns, if present, are too diffuse to register in daily prices; and (iii) *alignment* with core customer segments and communities is best assessed through operating outcomes rather than market value.

In terms of implications for policy and disclosure, because the equity-price channel is underpowered for campaign-level giving, simple improvements in disclosure — clear objectives, audited outcomes, consistent reporting windows — are valuable less for what they would reveal in prices than for enabling the bank-level, operating-outcome evaluation that the magnitudes call for. For regulators and standard setters, encouraging comparable, campaign-level reporting would lower measurement frictions in emerging markets without prescribing levels of giving.

It should be noted that our outcome is the stock price, a forward-looking proxy that aggregates expectations about multiple channels (deposits, fees, risk); a clean firm-level series on the dollar value of giving, which is not separately disclosed, would permit a dose–response test. We study a single, iconic campaign in one sector and country, so external validity beyond high-salience events and bank-intensive settings should be drawn cautiously. In terms of avenues for future research, we see four tractable extensions. (i) *Outcomes*: complement prices with operating variables — deposit inflows, new-account openings, card issuance, branch traffic — to detect reputational effects that daily prices cannot. (ii) *Granularity*: exploit bank-branch exposure to campaign intensity for within-bank identification. (iii) *Dynamic effects*: extend the event-study leads/lags to document anticipation and persistence at lower frequencies. (iv) *Comparative settings*: replicate the design in other emerging markets and for other recurring, high-visibility campaigns to map the conditions, if any, under which a price response emerges.

In sum, repeated participation in a salient national philanthropy campaign has no measurable association with the market valuation of a leading bank, once the analysis is conducted on stationary, market-benchmarked outcomes. The practical and methodological lesson is the same: the value of such campaigns, if it exists, must be sought in slow-moving operating and reputational channels, and measured with tools better powered than the daily share price.

CRediT authorship contribution statement

Marcelo J. Villena: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mauricio G. Villena:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Franco Antonucci:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Per-edition level-DID estimates (diagnostic)

For completeness and replicability we report the full per-edition (sample-splitting) difference-in-differences estimates on the normalized and standardized price, with and without controls. As shown in Section 6.3, these level-based estimates are not robust to serial-correlation-consistent inference or to the granularity of the time effects, and the per-edition normalized-price coefficients are additionally sensitive to within-window re-normalization. They are reported as a description of the level-specification artifact, not as estimates of a philanthropy effect.

Table A.1
Diff-in-diff analysis with normalized price, 2000–2010.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	2000	2002	2003	2004	2006	2007	2008	2010
Treatment	0.0228	−0.162***	−0.196***	0.147***	−0.0284	0.0188	0.0907***	0.159***
	(0.0369)	(0.0475)	(0.0271)	(0.0344)	(0.0187)	(0.0359)	(0.0161)	(0.0609)
Post	0.263***	−0.144***	0.226***	0.269***	0.426***	0.110***	−0.233***	0.299***
	(0.0410)	(0.0352)	(0.0306)	(0.0266)	(0.0170)	(0.0297)	(0.0220)	(0.0279)
DID	−0.203***	0.372***	0.0966**	−0.0292	0.0648**	−0.189***	−0.0406	−0.0372
	(0.0669)	(0.0561)	(0.0421)	(0.0447)	(0.0295)	(0.0510)	(0.0374)	(0.0649)
Constant	0.418***	0.582***	0.360***	0.268***	0.295***	0.531***	0.727***	0.296***
	(0.0300)	(0.0297)	(0.0225)	(0.0179)	(0.0127)	(0.0190)	(0.00953)	(0.0235)
Observations	266	261	407	404	472	356	480	324
R-squared	0.159	0.148	0.256	0.300	0.678	0.067	0.287	0.331

Note: Robust standard errors in parentheses.

Table A.2
Diff-in-diff analysis with normalized price, 2011–2020.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	2011	2012	2014	2015	2016	2017	2018	2020
Treatment	−0.228***	−0.0549*	0.0727**	−0.0628*	−0.0837***	−0.137***	0.0996***	−0.00190
	(0.0264)	(0.0297)	(0.0322)	(0.0374)	(0.0298)	(0.0354)	(0.0294)	(0.00611)
Post	−0.111***	−0.129***	0.0618*	−0.200***	0.180***	0.0968***	−0.0524*	−0.434***
	(0.0270)	(0.0282)	(0.0315)	(0.0301)	(0.0338)	(0.0258)	(0.0279)	(0.0114)
DID	0.219***	0.245***	−0.0350	0.399***	0.0774	0.121**	−0.0580	−0.0161
	(0.0483)	(0.0527)	(0.0520)	(0.0483)	(0.0512)	(0.0504)	(0.0438)	(0.0200)
Constant	0.654***	0.563***	0.514***	0.540***	0.415***	0.512***	0.464***	0.922***
	(0.0177)	(0.0190)	(0.0248)	(0.0246)	(0.0233)	(0.0207)	(0.0198)	(0.00387)
Observations	360	432	440	324	344	472	360	812
R-squared	0.108	0.074	0.018	0.223	0.146	0.092	0.046	0.718

Note: Robust standard errors in parentheses.

Table A.3
Diff-in-diff analysis with normalized price and controls, 2000–2010.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	2000	2002	2003	2004	2006	2007	2008	2010
Treatment	−0.598***	−0.144***	−0.173***	0.0390	−0.0151	−0.0563	0.122***	0.165***
	(0.0752)	(0.0440)	(0.0124)	(0.0412)	(0.0167)	(0.0382)	(0.0203)	(0.0409)
Post	−0.0626	−0.403***	0.00867	0.0560	0.107***	0.402***	0.0370	−0.136***
	(0.0672)	(0.0577)	(0.0337)	(0.0425)	(0.0234)	(0.0429)	(0.0386)	(0.0365)
DID	−0.0820	0.384***	−0.00513	−0.0252	0.0642***	−0.146***	−0.0723**	−0.0669
	(0.0610)	(0.0510)	(0.0260)	(0.0405)	(0.0213)	(0.0453)	(0.0349)	(0.0532)
Date	0.00363***	0.00367***	0.00356***	0.00283***	0.00365***	−0.00441***	−0.00305***	0.00763***
	(0.000591)	(0.000688)	(0.000453)	(0.000464)	(0.000218)	(0.000577)	(0.000335)	(0.000570)
Ratio P/B	0.600***	0.0570**	0.303***	0.108***	−0.0279***	0.0821***	−0.000234**	0.0705***
	(0.0659)	(0.0240)	(0.0161)	(0.0249)	(0.00726)	(0.0137)	(0.000107)	(0.0114)
Volume	−1.62e−09	7.45e−10*	7.06e−13	1.45e−10***	−9.17e−11*	1.37e−10***	−9.34e−12	2.95e−11***
	(1.05e−09)	(4.45e−10)	(5.36e−13)	(5.46e−11)	(5.03e−11)	(3.69e−11)	(4.84e−11)	(8.50e−12)
Constant	−54.60***	−56.71***	−57.18***	−46.15***	−61.78***	77.03***	54.90***	−141.2***
	(8.763)	(10.72)	(7.212)	(7.559)	(3.703)	(10.04)	(5.934)	(10.56)
Observations	266	261	407	404	472	356	480	324
R-squared	0.401	0.277	0.632	0.384	0.800	0.274	0.390	0.613

Note: Robust standard errors in parentheses.

Appendix B. Robustness of the abnormal-return results

This appendix reports the coefficients underlying the robustness checks summarized in Sections 6.4 and 6.6. Table B.1 gives the per-edition CAPM abnormal-return difference-in-differences: none of the sixteen editions is significant at the 5% level, nine of sixteen are positive, and the point estimates scatter between roughly −21 and +35 basis points. Table B.2 reports the pooled CAPM abnormal-return DID under alternative market benchmarks, beta estimation, event-window timing, sample exclusions, and single-comparison-bank contrasts; the coefficient is small (a few basis points per day) and statistically insignificant throughout.

Table A.4
Diff-in-diff analysis with normalized price and controls, 2011–2020.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	2011	2012	2014	2015	2016	2017	2018	2020
Treatment	−0.212***	−0.109***	−0.0868***	−0.0741	−0.161***	−0.103***	0.141***	−0.0502***
	(0.0282)	(0.0287)	(0.0302)	(0.0502)	(0.0272)	(0.0350)	(0.0337)	(0.0127)
Post	−0.142***	−0.0502	0.0979**	0.130**	0.00803	−0.0432	0.256***	−0.120***
	(0.0501)	(0.0488)	(0.0486)	(0.0507)	(0.0593)	(0.0337)	(0.0560)	(0.0146)
DID	0.208***	0.227***	−0.0503	0.396***	−0.0125	0.118**	−0.0627	−0.00745
	(0.0478)	(0.0531)	(0.0491)	(0.0504)	(0.0404)	(0.0498)	(0.0411)	(0.0156)
Date	0.000422	−0.000705	−3.76e−05	−0.00559***	0.00395***	0.00163***	−0.00439***	−0.00193***
	(0.000707)	(0.000564)	(0.000480)	(0.000680)	(0.000669)	(0.000471)	(0.000611)	(9.29e−05)
Ratio P/B	−0.0165	0.0627***	0.233***	−0.0120	0.199***	−0.0175	−0.0275**	0.0423***
	(0.0192)	(0.0215)	(0.0295)	(0.0405)	(0.0285)	(0.0157)	(0.0138)	(0.00538)
Volume	2.68e−10***	−1.95e−10	1.01e−11	−2.70e−10***	6.00e−11***	9.23e−11***	7.05e−11***	1.39e−11
	(5.79e−11)	(1.41e−10)	(1.83e−11)	(9.31e−11)	(1.49e−11)	(3.23e−11)	(1.71e−11)	(2.54e−11)
Constant	−7.276	13.94	0.742	114.2***	−81.77***	−33.65***	94.42***	42.93***
	(13.35)	(10.85)	(9.583)	(13.83)	(13.83)	(9.894)	(13.08)	(2.021)
Observations	360	432	440	324	344	472	360	812
R-squared	0.129	0.108	0.148	0.405	0.341	0.136	0.231	0.848

Note: Robust standard errors in parentheses.

Table A.5
Diff-in-diff analysis with standardized price, 2000–2010.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	2000	2002	2003	2004	2006	2007	2008	2010
Treatment	0.300**	−0.774***	−0.317***	−0.104	−0.0600	0.433**	0.164**	0.0948
	(0.136)	(0.206)	(0.101)	(0.150)	(0.0665)	(0.170)	(0.0744)	(0.216)
Post	0.857***	−0.501***	0.848***	0.892***	1.639***	0.425***	−0.941***	1.093***
	(0.137)	(0.152)	(0.104)	(0.103)	(0.0604)	(0.118)	(0.0929)	(0.109)
DID	−0.617**	1.479***	0.632***	0.210	0.120	−0.819***	−0.329*	−0.183
	(0.251)	(0.241)	(0.168)	(0.195)	(0.105)	(0.239)	(0.169)	(0.231)
Constant	−0.416***	0.264**	−0.423***	−0.442***	−0.820***	−0.225***	0.471***	−0.567***
	(0.106)	(0.131)	(0.0731)	(0.0666)	(0.0447)	(0.0747)	(0.0434)	(0.0934)
Observations	266	261	407	404	472	356	480	324
R-squared	0.126	0.125	0.274	0.227	0.703	0.044	0.269	0.279

Note: Robust standard errors in parentheses.

Table A.6
Diff-in-diff analysis with standardized price, 2011–2020.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	2011	2012	2014	2015	2016	2017	2018	2020
Treatment	−0.541***	−0.479***	0.0290	−0.929***	−0.288***	−0.267**	0.220	0.0450*
	(0.129)	(0.122)	(0.121)	(0.171)	(0.107)	(0.133)	(0.156)	(0.0237)
Post	−0.517***	−0.472***	0.179	−0.825***	0.592***	0.306***	−0.226*	−1.676***
	(0.117)	(0.108)	(0.110)	(0.117)	(0.119)	(0.105)	(0.121)	(0.0432)
DID	1.059***	0.958***	−0.0569	1.835***	0.575***	0.533***	−0.422*	−0.0878
	(0.232)	(0.216)	(0.218)	(0.225)	(0.211)	(0.197)	(0.232)	(0.0775)
Constant	0.264***	0.236***	−0.0912	0.418***	−0.296***	−0.153**	0.118	0.859***
	(0.0828)	(0.0756)	(0.0771)	(0.0947)	(0.0661)	(0.0738)	(0.0890)	(0.0147)
Observations	360	432	440	324	344	472	360	812
R-squared	0.069	0.057	0.007	0.194	0.153	0.062	0.036	0.724

Note: Robust standard errors in parentheses.

Table A.7
Diff-in-diff analysis with standardized price and controls, 2000–2010.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	2000	2002	2003	2004	2006	2007	2008	2010
Treatment	−1.416***	−0.687***	−0.274***	−0.537***	−0.0761	0.0224	0.274***	0.114
	(0.275)	(0.185)	(0.0558)	(0.172)	(0.0561)	(0.172)	(0.0886)	(0.144)
Post	−0.172	−1.674***	−0.158	0.0524	0.438***	1.637***	0.219	−0.580***
	(0.250)	(0.243)	(0.127)	(0.169)	(0.0737)	(0.173)	(0.166)	(0.141)
DID	−0.289	1.535***	0.439***	0.225	0.119	−0.592***	−0.449***	−0.281
	(0.237)	(0.217)	(0.124)	(0.177)	(0.0731)	(0.207)	(0.156)	(0.190)
Date	0.0116***	0.0166***	0.0147***	0.0112***	0.0137***	−0.0184***	−0.0132***	0.0291***
	(0.00225)	(0.00297)	(0.00183)	(0.00186)	(0.000718)	(0.00232)	(0.00140)	(0.00217)
Ratio P/B	1.649***	0.272***	0.582***	0.430***	0.0511*	0.433***	−0.000907*	0.230***
	(0.237)	(0.102)	(0.0692)	(0.0993)	(0.0263)	(0.0526)	(0.000477)	(0.0487)
Volume	−6.60e−09	3.70e−09*	1.31e−11***	5.53e−10***	2.91e−10	6.26e−10***	−2.36e−10	8.98e−11***
	(4.06e−09)	(1.99e−09)	(2.67e−12)	(1.95e−10)	(2.24e−10)	(1.46e−10)	(2.14e−10)	(2.26e−11)
Constant	−175.5***	−258.9***	−235.7***	−183.4***	−233.6***	319.5***	233.9***	−539.4***
	(33.30)	(46.25)	(29.11)	(30.29)	(12.21)	(40.38)	(24.82)	(40.19)
Observations	266	261	407	404	472	356	480	324
R-squared	0.288	0.278	0.461	0.317	0.827	0.299	0.375	0.573

Note: Robust standard errors in parentheses.

Table A.8
Diff-in-diff analysis with standardized price and controls, 2011–2020.
Source: Own elaboration based on data obtained from the Santiago Stock Exchange. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Variables	2011	2012	2014	2015	2016	2017	2018	2020
Treatment	−0.671***	−0.799***	−0.367***	−1.191***	−0.601***	−0.397***	0.177	−0.0258
	(0.126)	(0.116)	(0.121)	(0.221)	(0.0957)	(0.139)	(0.179)	(0.0505)
Post	−0.726***	−0.224	0.443**	0.523**	−0.0641	−0.171	1.028***	−0.463***
	(0.209)	(0.193)	(0.200)	(0.205)	(0.199)	(0.135)	(0.267)	(0.0565)
DID	0.915***	0.839***	−0.0964	1.778***	0.213	0.513***	−0.433**	−0.0874
	(0.214)	(0.213)	(0.212)	(0.229)	(0.165)	(0.192)	(0.218)	(0.0623)
Date	0.00492	−0.00141	−0.00222	−0.0220***	0.0153***	0.00552***	−0.0177***	−0.00772***
	(0.00307)	(0.00222)	(0.00192)	(0.00284)	(0.00243)	(0.00192)	(0.00287)	(0.000370)
Ratio P/B	0.423***	0.411***	0.582***	0.433***	0.785***	0.152**	0.0743	0.0607***
	(0.0800)	(0.0762)	(0.0941)	(0.152)	(0.104)	(0.0650)	(0.0619)	(0.0205)
Volume	5.17e−10	−4.63e−10	4.43e−11	−3.58e−10*	1.28e−10***	2.25e−10**	2.35e−10***	−2.06e−10**
	(3.20e−10)	(5.06e−10)	(5.96e−11)	(2.05e−10)	(3.51e−11)	(1.08e−10)	(5.41e−11)	(9.80e−11)
Constant	−93.87	26.30	42.80	446.6***	−319.6***	−116.6***	378.7***	169.0***
	(58.04)	(42.62)	(38.25)	(57.80)	(50.32)	(40.36)	(61.47)	(8.050)
Observations	360	432	440	324	344	472	360	812
R-squared	0.137	0.122	0.072	0.362	0.365	0.092	0.169	0.847

Note: Robust standard errors in parentheses.

Table B.1
Per-edition CAPM abnormal-return DID.

Edition	DID (bps/day)	*p*-value	Edition	DID (bps/day)	*p*-value
2000	+30.1	0.314	2011	+9.9	0.760
2002	−8.0	0.810	2012	−10.6	0.629
2003	+34.6	0.359	2014	+5.8	0.712
2004	−12.1	0.650	2015	−19.0	0.325
2006	+5.7	0.784	2016	−16.1	0.440
2007	+26.0	0.283	2017	−7.3	0.703
2008	+5.1	0.903	2018	+2.4	0.887
2010	−21.2	0.532	2020	+22.3	0.437

Per-edition DID coefficient on the CAPM abnormal return (IGPA market model), in basis points per day, with heteroskedasticity-robust *p*-values. None is significant at the 5% level; nine of sixteen are positive.

Table B.2
Pooled CAPM abnormal-return DID: robustness.

Specification	DID (bps/day)	*p*-value
Baseline (IGPA, full-sample beta)	+6.01	0.295
IPSA benchmark	+5.79	0.315
Pre-event-window beta ($[-250, -30]$)	+4.22	0.518
Event start shifted −14 trading days	+5.44	0.282
Event start shifted −7 trading days	+5.85	0.280
Event start shifted +7 trading days	+7.42	0.237
Event start shifted +14 trading days	+5.01	0.469
Exclude 2000–2004 editions (approximate dates)	+2.79	0.655
Exclude M&A editions (2008, 2015, 2016)	+8.21	0.188
Single comparison bank: BCI	+7.46	0.287
Single comparison bank: Itaú	+2.04	0.812
Single comparison bank: Santander	+8.10	0.245

Pooled DID coefficient on the CAPM abnormal return, in basis points per day, standard errors clustered by date. "Single comparison bank" restricts the comparison group to one bank at a time. No specification is significant at conventional levels.

Data availability

Data will be made available on request.

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