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Curb your enthusiasm on sign-in bonuses: evidence from Coinbase's Super Bowl campaign

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"Moderando el entusiasmo respecto a los bonos por registro: evidencia de la campaña de Coinbase en el Super Bowl"

Resumen

Esta tesis explora el impacto de una campaña de bonos por registro en el uso de aplicaciones móviles, utilizando la campaña de marketing de Coinbase durante el Super Bowl de 2022 como caso de estudio. Las campañas de marketing pueden afectar el comportamiento del usuario en diferentes etapas de su "trayectoria de uso": conocer la aplicación, descargarla y usarla. Basándonos en datos de actividad de usuarios a nivel diario, y utilizando el método de control sintético para una evaluación de impacto rigurosa, encontramos que la campaña tuvo un efecto significativo a corto plazo en las descargas de la aplicación, pero no tuvo efecto en su utilización posterior. Estos resultados siembran dudas respecto a la rentabilidad de dichas estrategias de marketing.

Palabras clave: marketing de apps, descuentos, bono de registro, actividad de usuarios, control sintético

"Curb your enthusiasm on sign-in bonuses: evidence from Coinbase's Super Bowl campaign"

Abstract

This thesis explores the impact of a sign-in bonus campaign on mobile app usage, using Coinbase's 2022 Super Bowl marketing campaign as a case study. Marketing campaigns can affect user behavior over different stages of their "customer journey": getting to know the app, downloading and engaging with it. Based on user activity daily data and using the synthetic control method for rigorous impact evaluation, we find that the campaign had a significant short-term effect on app downloads, but no effect on posterior user engagement. These results cast doubts on the profitability of such marketing strategies.

Keywords: app marketing, discounts, sign in bonus, user engagement, synthetic control

JEL codes: C21, M21, M31, M37

1 Introduction

The growth of mobile applications (or simply "apps") has been a major driving force behind the rapid development of the digital economy. In recent years, apps have become indispensable tools for millions of people worldwide, providing them with a convenient and accessible way to perform various tasks and access information (Natarajan, 2017). As a result, there has been a significant increase in the number of businesses and entrepreneurs looking to develop and launch their mobile applications to reach new customers and expand their markets.

Given the increasing importance of mobile applications in the global economy, businesses and entrepreneurs must understand the strategies that can help them achieve growth and success. Research on app growth strategies becomes relevant in this context since it provides valuable insights and guidance on effectively promoting, marketing, and monetizing mobile applications. Building evidence-based knowledge on this topic can help app-related companies identify the most effective marketing channels, understand user behavior, and create customer acquisition and retention strategies.

The present investigation addresses the challenge of evaluating the impact of a particular type of marketing strategy (offering sign-in bonuses to new users) in order to properly assess its potential and its limitations as a driver for business growth. We will focus on understanding whether these strategies have a lasting impact on user behavior or if their effectiveness is just superficial and transitory. For this purpose, an event study of Coinbase's 2022 Super Bowl marketing campaign will be carried out, analyzing it within the "customer journey" theoretical framework, and applying an econometric methodology (the synthetic control method) for rigorous impact evaluation. In this way, we expect that the particular conclusions from this study can contribute to more general theoretical and practical models for app business growth.

Previous studies, such as Askalidis (2018) and Wohllebe, Stoyke and Podruzsik (2020), have approached the issue of impact evaluation of marketing strategies for mobile app growth using rigorous econometric techniques and experimental designs. Those studies find interesting causal relations that can be further analyzed to generate valuable insights for decision-makers. The present study intends to contribute to this line of research by using a novel methodology within this particular literature, and by diving deeper into the effects of sign-in bonuses on user behavior. The investigation's main findings can be summarized in two points. First, sign-in bonuses can increase the volume of app downloads, but its effect is short-lived over time; and, second, users attracted by monetary incentives may not be the ones who keep engaging with the platform after they cashed their bonuses.

The rest of the paper is organized as follows. Section 2 presents the "customer journey" theoretical framework, together with background facts about the mobile app economy, cryptocurrency exchanges, and Super Bowl marketing campaigns. Section 3 discusses the synthetic control approach as an identification strategy. Section 4 describes the analyzed data and its sources. Section 5 presents the results of the synthetic control method implementation and a series of robustness checks. Finally, section 6 summarizes the main conclusions of the investigation.

2 Background

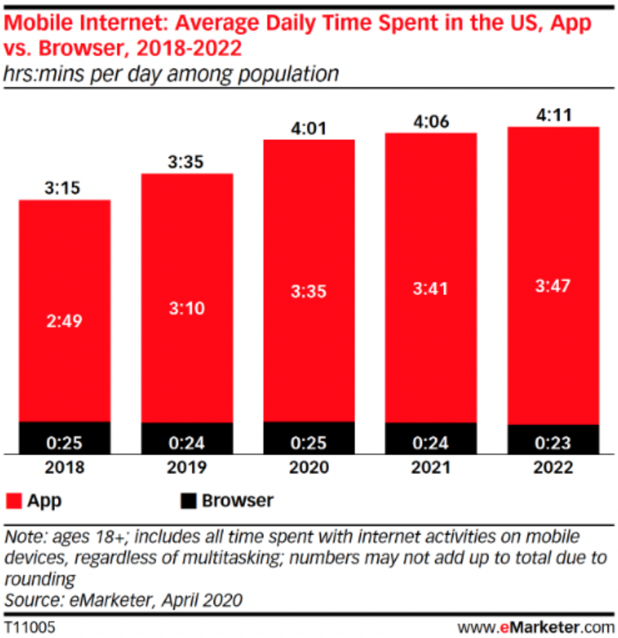
2.1 App Economy and Cryptocurrencies

The size and relevance of the "app economy" have been extensively documented over the last ten years in works such as Stocchi et al. (2021), Mondal (2019), and Natarajan (2017). According to Data AI (2022), 230 billion app downloads were generated during 2021 (worldwide), resulting in $170 billion in consumer spend and 3.8 trillion hours of app usage. That same year, 2 million new apps were released in Google Play and Apple App Store (the two leading app stores in terms of users and downloads), bringing the total number of available apps to over 21 million (Data AI, 2022). Regarding app usage, EMarketer (2020) estimates that US adults spend, on average, almost four daily hours on the mobile internet, with 88% of that time within apps (see Figure 1).

As Natarajan (2017) states, the app economy revolution is fueled by the practical and user-friendly environments that apps provide to perform almost any online task (communicating, shopping, playing games, watching video content and others). On the supply-side, companies also have incentives to interact with customers through mobile apps since "once applications are downloaded to the user's mobile phone, reaching the customers through sending promotional offers, announcing new products, sending reminders and other marketing efforts by the retailers influence the attitude of the users of the technology" (Natarajan, 2017). In this way, apps create self-reinforcing loops of customer engagement, and app companies compete with each other for a larger piece of the overall engagement.

Mobile apps are particularly relevant in the context of the recent crypto-currency market de-

Figure 1: Mobile App Usage in the US



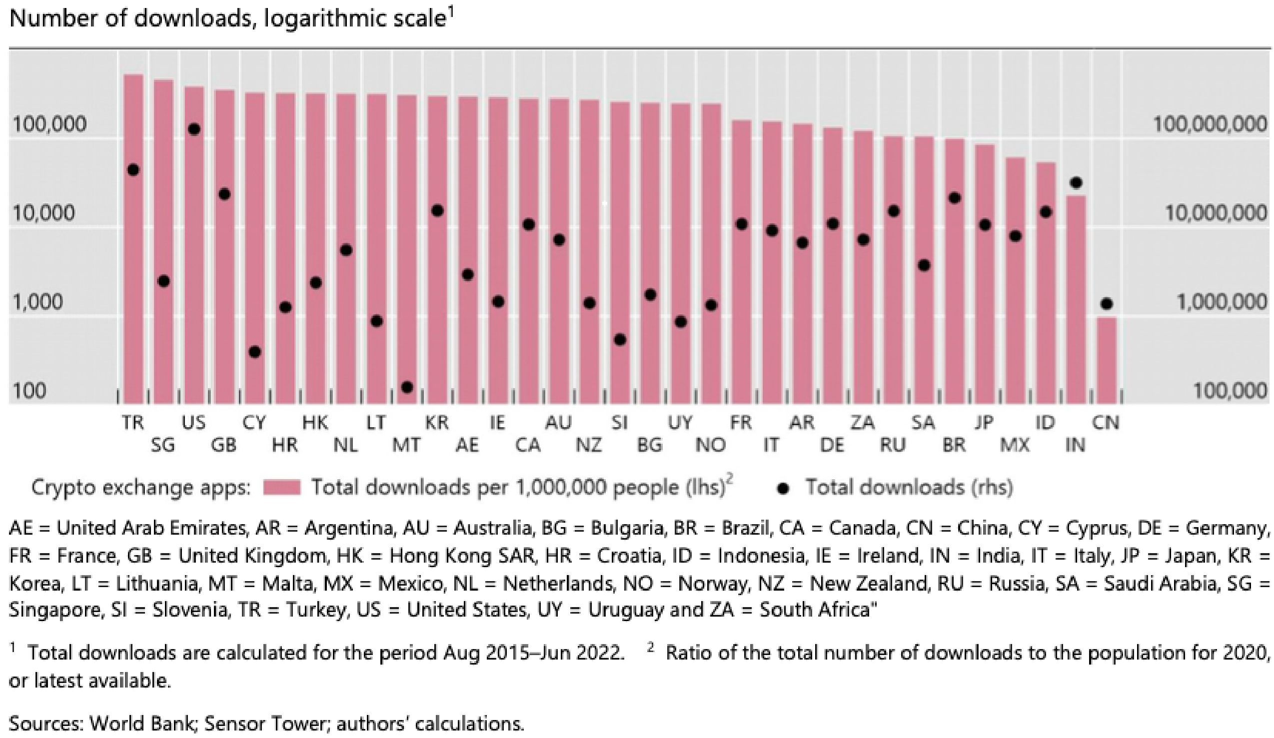
Source: eMarketer (2020)

velopment. As Auer et al. (2022) document, the rise in crypto-currencies prices between 2015 and 2021 was accompanied by major growth in daily active users (DAUs) of the top crypto-exchanges mobile apps, which grew from 119,000 to 32.5 million in that period, with a cumulative total of 565 million app downloads (most of them occurring during the 2020-2021 Bitcoin price peaks). Figure 2, taken from Auer et al. (2022), shows that crypto exchange apps penetration (in terms of downloads per million inhabitants) is relevant in both developed and developing economies.

IMF (2022) defines these crypto exchanges as companies or institutions that "facilitate the buying and selling of unbacked crypto assets and provide much wider services than traditional securities exchanges" (these extra services include asset custody and even issuing their own currencies). Since the revenue generated from the fees charged to users for these services is directly associated with total users and transactions volume, crypto exchanges compete to attract new users to their apps. This competition has been documented to occur by means of advertising strategies (Icoda, 2021), sign-in or welcome bonuses (Boxmining, 2020), new features or coins offerings (Qoden, 2019; Forecast, 2021), increasing transparency and security (Toptal, 2021) and even inflating trading volumes to signal higher liquidity (Amiram, 2021).

The following subsection proposes a more general theoretical framework that will allow us to

Figure 2: Crypto Exchange Apps Market Penetration



Source: Auer et al. (2022)

analyze these strategies for user base growth, paying particular attention to sign-in bonuses or coupons.

2.2 Marketing Strategies and "Customer Journey" Framework

In the context of this flourishing app economy and crypto market, app companies strive to rapidly grow a solid user base and generate revenue from it. As Stocchi et al. (2021) and Appinventiv (2022) indicate, companies execute different marketing actions in order to get potential users to interact with their apps: advertising (in traditional media, websites, or other apps), keywords selection in order to appear in search engines' top places (SEO - Search Engine Optimization), app store optimization (ASO), viral campaigns in social media, making influencers interact with the app, email marketing, push notifications, special offers, and discounts, among others. The goals and results of these different practices can be analyzed in a systematic way using the "customer journey" framework proposed by Lemon and Verhoef (2016) and updated and expanded by Stocchi et al. (2021).

The "customer journey" framework synthesizes the user's experience and interactions with an app into three main “journey stages” (Stocchi et al., 2021):

1. Pre-adoption stage: refers to every user interaction with the app (or the brand who owns it) before installing it. In this stage, the individual user’s characteristics that make him or her more propense to install the app play a significant role, as well as the marketing actions executed by companies to raise awareness of their apps and enhance the user’s existing predispositions.

2. Adoption stage: starts with the user’s decision-making process when choosing an app at an online app store, and goes through the steps of downloading, installing, registering, and performing the first in-app experiences (exploring the features and making the first transactions).

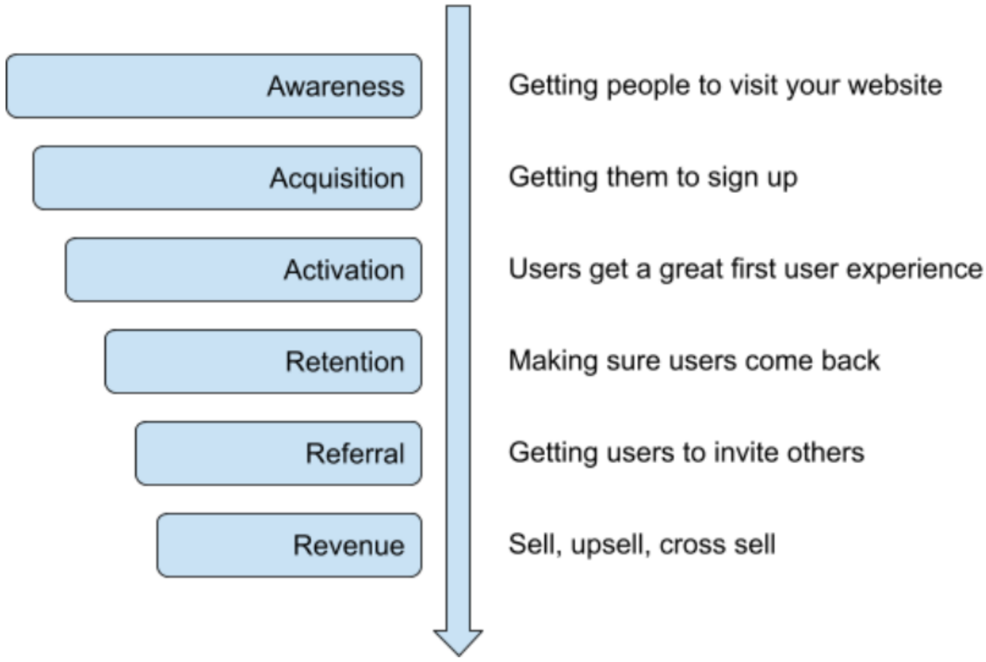
3. Post-adoption stage: involves all further experiences after the initial ones. User engagement and the “stickiness” or brand loyalty that results from it are the primary outcomes from this stage.

This “customer journey” framework bears a notorious resemblance to the “pirate funnel” framework commonly used by “growth hacking” practitioners (Rowlinson, 2020; Tuladhar, 2022), which also describes the user’s relationship with an app and it is synthesized in Figure 3. The pirate funnel’s “awareness” step is analogous to the customer journey’s pre-adoption stage, while the “acquisition” and “activation” steps correspond to the adoption stage. Finally, the “retention”, “referral” and “revenue” stages at the pirate funnel may be included in the customer journey’s post-adoption stage.

In the scope of this investigation, the effect of different marketing actions can be analyzed using any of these two conceptual frameworks: “customer journey” and “pirate funnel”. Specifically, we will be interested in understanding if marketing strategies based on discounts, giveaways, coupons, or sign-in bonuses (which constitute a specific kind of coupon) are effective in driving users across the whole journey, or if their effectiveness is limited to the adoption or activation stages. This is particularly relevant because, if marketing campaigns are seen as an investment (rather than a fixed cost), the return on those investments depends on the capability of the campaigns to drive revenue in the final stage of the funnel.

The use of discounts, coupons, or giveaways as a marketing instrument is widely extended across many industries, and the economics and marketing science literature has documented

Figure 3: “Pirate Funnel” (AAARRR)



Source: Tuladhar (2022)

and studied this practice. Narasimhan (1984) provides a theoretical model that shows how discount campaigns constitute a price discrimination tool used to reach particular consumer segments with higher price-elasticity demand. Empirical studies, such as Bawa and Shoemaker (1987) and Inman and McAlister (1994) find positive effects of discounts on total sales and analyze how different campaign designs may modify the effect's magnitude.

With the rise of the digital economy, one stream of the marketing science literature has studied how coupons distributed through mobile apps affect sales in physical stores (Beeck and Toporowski, 2017; Lee and Choeh 2020), while another stream, closer to this investigation, has focused on how app store discounts in paid apps or coupons for in-app purchases/transactions affect apps downloads and usage [1].

In this second stream of literature, Chaudhari and Byers (2017) find that Amazon's “App of the Day” discounts program for paid apps has positive and significant short-term effects on the number of users who download the promoted apps. Following this line of research, Askalidis

[1] In this section, we will use the term “paid app” to refer to apps that charge users for downloading them, and “non-paid app” to refer to apps that are free to download but make revenue out of in-app transactions or purchases. Crypto exchanges fall into this second category, since they charge their users for the in-app transactions they perform after downloading the app.

(2018) uses a difference-in-differences identification strategy to show how special price discounts on paid apps at the Apple store have a positive effect on the promoted apps' installs volume; and Liu et al. (2019) find similar results using the volume of app ratings as a proxy for downloads. Putting these results in the context of the customer journey framework, they provide clear evidence of the discount strategies' effectiveness in driving users through the adoption/acquisition stages. Still, the effects on the following post-adoption/retention stages are not assessed.

The work of Wohllebe, Stoyke and Podruzsik (2020) dives deeper into customer journeys in non-paid apps. Using an experimental framework (serving differentiated ads and promotions to different user groups), they find significant positive effects of coupons on downloads, but null and even negative effects on posterior app usage after download. The authors relate these findings to the hypothesis stated by Bawa and Shoemaker (1987), who found that branded coupons' effects are larger on users who had a higher prior probability of purchasing the brand who issued the coupons (in the context of traditional physical retail stores). Wohllebe, Stoyke and Podruzsik (2020) suggest that this hypothesis stays relevant in the app economy (particularly in non-paid apps) since actual sales and revenue generation occur in the post-adoption stage of the customer journey. Downloading a non-paid app and signing in does not constitute a sale per se but just an enabler for future sales. The present study can be encompassed within this line of research since it evaluates the effects of "sign-in bonuses" (a particular kind of coupon) across different customer journey stages. In particular, we will analyze the effect of Coinbase's sign-in bonus campaign during the 2022 Super Bowl, which will be introduced in the following section.

2.3 Super Bowl Marketing Campaigns

The U.S. National Football League Finals (popularly known as "Super Bowl") is one of the top sports events in the world in terms of TV audience, and its relevance and implications for advertising have been widely studied in the marketing literature (Hartmann and Klapper, 2017; Davidowitz et al., 2016; Reiley and Lewis, 2013). As Hartmann and Klapper (2017) document: "Four of the five most-watched telecasts ever were Super Bowls. The 2012 broadcast was the most watched telecast in history [2], with 54% of U.S. households tuning in. The cost of

[2]The 2012 finals of the National Football League were disputed between the New York Giants and the New England Patriots on February 5th of that year. The Giants defeated the Patriots by the score of 21–17.

airing a 30-second spot during the game has grown [from $3 million in 2012] to nearly $5 million [in 2017]". Although being eminently a US phenomenon, millions around the world watch the Super Bowl especially due to its traditional "half-time show", in which top artists and musicians usually perform (Statista, 2022). These facts explain why the Super Bowl constitutes an outstanding advertising opportunity for companies wanting to position their brands and products.

The 2022 Super Bowl (disputed on February 13th between Cincinnati Bengals and Los Angeles Rams) was no exception. According to Marketing Charts (2022), 99 million viewers in the US watched the Super Bowl, with 72% of homes with TVs tuning the telecast. The 30 seconds slots for ads during the broadcast reached a cost of $6.5 million, which represented an 18% increase versus the previous year's costs. However, the novelty in this edition was that four crypto exchange companies were advertising in a Super Bowl for the first time: Coinbase, FTX, Crypto.com, and eToro presented 30-second video ads during the telecast (iSpot.tv, 2022). These advertisements can be interpreted as another sign of the "crypto euphoria" developed during the preceding years (Auer et al., 2022).

Coinbase's ad was one of the favorites among spectators and critics. Under the slogan "Less talk, more Bitcoin", the commercial was both minimalistic and eye-catching. It included a QR code that, when scanned from a mobile phone, led users to a website where they could download the app and receive a sign-in bonus of $15-worth of free Bitcoin, cashed within the Coinbase app (Cointelegraph, 2022). This sign-in bonus was available for every new user who joined the platform during the 48 hours after the ad release. According to LXA (2022), 117 million watched the ad worldwide, from which 20% scanned the QR code and 10% signed up, leading to almost 500.000 new Coinbase users. Cointelegraph (2022) reports that the whole marketing action costed around $14 million [3].

The present investigation will inquire into the efficiency of this particular marketing investment. Taking as a reference the customer journey framework presented in the previous sections, the crypto exchange business model requires marketing strategies not only to be successful at the adoption stage of the journey, but also at the post-adoption stage, since revenue from users is generated in that last stage. For this purpose, a synthetic control identification strategy (pre-

[3] It may be worth noticing that, although other three crypto apps presented ads during the 2022 Super Bowl, Coinbase was the only one which implemented a sign-in bonus campaign associated with their ad. Therefore, we will center our attention exclusively on Coinbase's app downloads and active users

sented in the following section) will be used to assess the impact of the Super Bowl marketing action on the Coinbase app's downloads (as a measure of adoption results) and active users (as a measure of post-adoption results).

3 Identification Strategy: The Synthetic Control Method

Identifying the causal effects of marketing campaigns has a crucial relevance for managers and investors since this allows them to evaluate the effectiveness of alternative marketing strategies and, based on that, make decisions that maximize the return on the investment. Marketing departments (especially in big companies) usually evaluate the effectiveness of their campaigns through experimental approaches, by running randomized controlled trials among customers to test different features of their products or communications (as described in Wohllebe, Stoyke and Podruzsik, 2020); or by segmenting different cities, regions, audiences or products and performing diff-in-diff analysis on segments "treated" by the campaigns versus the "non-treated" ones (see Askalidis, 2018). The usual process is making small tests first, with alternative campaign features, to check what performs best; and then running the definitive version on a larger scale.

However, a challenge appears when big one-time marketing campaigns (such as the ones executed at the Super Bowl) have to be evaluated, since the possibilities for randomized controlled trials or audience segmentation are vastly reduced, and unobservables may distort simple before-after analysis. In this context, the synthetic control method developed by Abadie et al. (2010) becomes an interesting approach for impact evaluation.

The synthetic control method's logic is similar to the diff-in-diff approach. However, it involves creating a weighted combination of other units (in this case, crypto exchange apps) that have not been affected by the treatment (giving sign-in bonuses) in order to simulate the characteristics of the unit that has been treated (Coinbase). This is done by assigning weights to each of the comparison units (also referred to as "donors") based on how well they match the characteristics of the treated unit. The method computes these weights so that they minimize the difference in pre-intervention outcomes between the treated unit and the donors. These weights are then used to build a synthetic version of the treated unit that simulates what would have happened if it hadn't received the treatment. The treatment's impact is finally estimated as the difference between the treated unit's real and synthetic outcomes.

The method can be formally described in the following way: suppose there are $J+1$ units (apps), indexed by $i = 1, \dots, J+1$; over T time periods indexed by $t = 1, \dots, T$. Only unit $i = 1$ is affected by the treatment (executing a sign-in bonus campaign), and the remaining J units are the control units unaffected by the treatment (the "donor pool"). There are T_0 number of pre-treatment time periods and T_1 post-treatment periods, so that $T_0 + T_1 = T$.

The effect of the treatment for unit i at time t is given by $\alpha_{it} = Y_{it}^{I} - Y_{it}^{N}$, where Y_{it}^{I} is the outcome variable (downloads or active users) for unit i if it is exposed to the treatment in period t, and Y_{it}^{N} is the outcome for the same unit and time period in the absence of treatment. Since only unit $i = 1$ is treated, we need to estimate $\alpha_{iT0}, \dots, \alpha_{iT}$. The outcomes for the pre-treatment period can be estimated using the following factor model:

$$Y_{it}^{N} = \delta_t + \theta_t X_i + \lambda_t \mu_i + \epsilon_{\text{ït}}$$

where δ_t represents time-specific effects (factors), X_i is the vector of k covariates unaffected by treatment (which may include the values of pre-intervention outcomes), θ_t is a vector of unknown time-specific parameters, λ_t are unobservable common factors, μ_i are unit-specific unobservables, and $\epsilon_{\text{ït}}$ are zero-mean transitory shocks.

Based on this model, the synthetic control method aims to build the counterfactual Y_{it}^{N} using the outcomes of units unaffected by the treatment. Letting $W = (w_2, \dots, w_J + 1)'$ be a $(J \times 1)$ vector of weights such that $0 \leq w_i \leq 1$ for $i = 2, \dots, J+1$ and $\sum_{i=2}^{J+1} w_i = 1$, then the following synthetic counterfactual for the treated unit can be defined (based on the non treated units):

$$Y_{1t}^{N} = \sum_{i=2}^{J+1} w_i Y_{it}$$

In this way, different values for the W vector represent different and alternative synthetic controls for the treated unit. Abadie et al. (2010) prove that if the number of pre-intervention periods in the data is large relative to the scale of the transitory shocks and we can choose a W^* such that:

$$\sum_{i=2}^{J+1} w_i^* Y_{it} = Y_{1t} \ \text{ for } t = 1, \dots, T_0$$

and

$$\sum_{i=2}^{J+1} w_i^* X_i = X_1$$

, then $\hat{\alpha}_{1t} = Y_{1t}^I - \sum_{i=2}^{J+1} w_i^* Y_{it}$ is an unbiased estimator of the treatment effect α_{1t}.

Implementing the algorithm developed by Abadie et al (2011), the optimal weights are chosen by finding the vector W^* that minimizes the square difference between the vector of pre-treatment covariates of the treated unit (in our case, Coinbase), and the pre-treatment covariates of the donor pool (the rest of the crypto exchange apps). Formally, the optimal weights are the result of the following minimization problem:

$$Min \ \ ||X_1 - X_0 W||_V = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)}$$

, where X_0 is a $(k \times j)$ matrix that contains the k different pre-treatment covariates for the J units in the donor pool; X_1 is a $(k \times 1)$ vector which contains the k different pre-treatment covariates for the treated unit; and V is a $(k \times k)$ diagonal, symmetric and positive semidefinite matrix which reflects the relative importance of the variables in X_0 and X_1. The matrix V is chosen so that it minimizes the mean squared error (MSE) of $\hat{\alpha}_{1t}$. This is achieved by choosing a V matrix such that the root mean squared prediction error (RMSPE) is minimized for pre-intervention periods, being RMSPE defined as:

$$RMSPE = \frac{1}{T_0} \sum_{t=1}^{T_0} \sqrt{(Y_{1t} - \sum_{i=2}^{J+1} w_i(V) Y_{it})}$$

The following section describes the data used as input for the synthetic control method. In Section 5, this methodology will be applied to build synthetic counterfactuals for the Coinbase app's downloads and active users after the sign-in bonus campaign launched during the 2022 Super Bowl. These counterfactuals will be compared against the actual outcomes to assess the campaign's impact.

4 Data

The data on downloads and usage of crypto apps (the outcome variables) comes from Data.AI, a proprietary app intelligence data provider. This dataset is similar to the one used by Auer et al. (2022). Data.AI (as well as other data platforms such as Sensor Tower or AppTweak) collects daily data on downloads, usage, ratings, reviews, and other indicators for apps both in the Google Play and Apple stores, in 103 countries.

Data on downloads do not include app updates or app re-downloads from the same account (for example, when a user downloads the app on another device). In this way, Data.AI avoids inflating the downloads number. The "active user" metric is defined "as any user that has at least one session on an app over a specific time period (...). If a user has more than one session over the selected time period, they will still only count as one active user for that time period" (Bauer et al., 2022). Although this metric may not completely reflect deeper interaction with the app (such as making deposits or buying crypto), it still allows comparing user engagement in a standardized way across different apps (since the "app open" or new session event is the same for all apps).

Our empirical analysis considers data on 39 crypto-related apps at a daily frequency between December 1st, 2021, and March 19th, 2022. This allows us to analyze trends for 75 days before and 34 days after the Super Bowl. Data is aggregated globally for the analysis, since access to crypto apps has almost no country-based restrictions (although some apps may face bans in particular countries), and interest in cryptocurrencies is widely spread worldwide (Auer et al., 2022). To select the sample of apps, we selected the top crypto exchange apps (in terms of downloads and active users) from the Data.AI ranking and expanded this selection with other fintech apps that, although not exclusively focused in cryptos, offer the possibility of buying and selling cryptocurrencies within their platforms.

As pre-treatment covariates, we use the following variables:

1. The Google Search trends for each of the selected apps' names during the analyzed time period. Choi and Varian (2012) define Google Search trends data as a "time series index of the volume of queries users enter into Google in a given geographic area. The query index is based on query share: the total query volume for the search term in question within a particular geographic region divided by the total number of queries in that region

Table 1: Summary Statistics for Selected Variables and Apps (Dec. 1st, 2021 - Mar. 19th, 2022)

App	Downloads (K)				Active Users (K)				Google Trends Index				Downloads US (K)				Active Users US (K)				Lft*
	Min	Mdn	Avg	Max	Min	Mdn	Avg	Max	Min	Mdn	Avg	Max	Min	Mdn	Avg	Max	Min	Mdn	Avg	Max	
Binance	93	129	133	253	15,788	18,396	18,631	23,222	18.20	24.66	25.05	40.43	2	4	4	8	155	205	208	278	51
Binance.US	1	3	3	6	68	102	107	168	0.00	0.08	0.07	0.16	1	3	3	6	67	100	104	163	25
BitMart	1	2	2	7	258	401	424	735	0.12	0.32	0.36	3.87	0	1	1	3	15	25	25	37	45
Bitstamp	0	1	1	2	30	40	56	256	0.08	0.24	0.26	0.64	0	1	1	2	4	7	8	13	31
Bittrex	0	0	1	1	29	48	50	85	0.12	0.28	0.29	0.52	0	0	0	0	0	1	1	1	25
Blockchain	6	9	9	11	133	230	244	441	0.00	0.04	0.04	0.16	2	3	3	4	24	39	38	51	108
Blockfi	0	1	1	3	52	114	120	226	0.28	0.44	0.48	1.24	0	1	1	2	27	45	44	60	21
Bybit	7	14	15	29	233	338	356	736	0.64	1.00	1.05	2.35	0	1	1	1	4	6	7	10	27
Cash App	30	91	91	138	9,843	11,474	11,494	13,208	7.33	9.59	9.57	13.32	26	87	86	134	9,780	11,383	11,411	13,115	99
Coinbase	32	64	62	225	3,862	5,923	5,783	8,138	6.83	12.48	12.65	23.54	11	28	27	189	1,906	3,095	3,063	4,149	107
CoinDCX	10	61	53	96	1,568	2,070	2,062	2,578	0.20	0.60	0.63	1.16	0	0	0	0	0	0	0	1	15
CoinMktCap	12	19	22	43	1,895	2,562	2,578	3,447	0.00	0.12	0.12	0.24	1	2	2	4	110	155	155	231	34
CoinSwitch	8	34	35	61	1,356	1,943	1,930	2,380	0.04	0.20	0.23	0.60	0	0	0	0	0	0	0	0	20
Cointelegraph	0	0	0	2	17	44	56	248	0.16	0.36	0.38	1.12	0	0	0	0	0	1	1	2	44
Crypto.com	53	89	91	152	2,255	2,819	2,892	3,947	1.77	3.30	3.37	6.11	8	24	24	56	434	643	632	931	53
eToro	12	19	19	26	1,028	1,611	1,568	1,987	1.73	2.77	2.75	4.33	1	1	2	6	40	82	81	129	99
Exodus	4	5	5	7	207	292	302	449	0.00	0.04	0.03	0.12	1	1	1	2	46	59	59	76	32
FTX	6	11	12	30	406	543	534	713	1.41	2.12	2.19	6.42	0	0	0	0	0	0	0	0	33
Gemini	2	7	7	11	57	88	105	330	0.00	0.00	0.02	0.12	1	5	4	8	49	66	69	108	38
Kraken	2	4	4	10	123	166	177	330	0.00	0.00	0.02	0.36	1	1	1	4	23	34	34	48	17
KuCoin	5	33	34	76	1,135	1,545	1,550	2,141	1.32	2.08	2.14	3.99	1	4	4	7	102	144	142	179	45
Luno	5	9	9	25	431	586	592	837	0.00	0.00	0.01	0.08	0	1	1	15	0	1	7	55	88
OctaFX	35	51	53	96	298	564	582	1,051	0.24	0.68	0.67	1.12	0	0	0	2	0	1	2	9	45
OKX	6	9	9	21	318	560	561	834	0.04	0.40	0.40	1.72	0	1	1	1	4	6	6	11	50
Paxful	3	4	4	5	9	27	40	237	0.28	0.52	0.53	1.00	1	1	1	1	1	1	1	2	34
PayPal	172	228	231	346	8,742	10,675	10,531	12,405	49.00	71.00	70.60	100.00	16	53	53	75	3,969	4,801	4,755	5,595	122
Phemex	1	3	3	9	12	45	49	113	0.00	0.16	0.22	0.92	0	0	1	3	2	3	3	7	24
Pionex	1	2	3	7	102	168	172	277	0.04	0.20	0.19	0.36	0	1	1	4	20	28	29	44	27
Revolut	29	39	40	58	4,827	6,237	6,105	7,209	2.50	4.64	4.72	7.36	1	2	2	4	37	72	71	102	81
Robinhood	5	12	12	21	2,507	4,339	4,141	5,637	1.95	4.01	4.10	10.28	5	12	12	21	2,353	3,940	3,789	4,990	79
SoFi	2	4	4	10	119	235	238	349	0.00	0.00	0.01	0.16	0	0	0	0	0	0	0	0	59
Stash Invest	7	15	16	24	286	442	431	557	0.00	0.00	0.02	0.12	7	15	16	24	286	442	431	557	77
Trade Republic	5	14	14	33	392	657	642	853	0.40	0.84	0.91	2.27	0	0	0	0	0	0	0	0	43
Trust	35	47	51	103	2,532	3,159	3,297	4,000	0.00	0.12	0.12	0.40	1	5	5	9	162	229	232	312	53
Uphold	2	4	4	5	206	311	309	395	0.00	0.00	0.01	0.16	1	2	2	3	87	114	112	139	74
Venmo	14	46	46	63	5,223	6,202	6,201	7,389	4.20	6.04	6.16	10.78	14	46	46	63	5,221	6,201	6,200	7,386	142
Voyager	2	6	8	20	142	180	189	288	0.00	0.00	0.01	0.08	0	0	0	0	0	0	0	0	37
WazirX	6	16	16	39	2,693	4,480	4,276	6,167	0.64	1.36	1.39	2.79	0	0	0	0	0	0	0	0	48
Webull	4	7	9	18	667	1,325	1,235	1,729	0.44	1.00	0.99	1.64	3	6	7	15	345	609	579	770	123

Source: Data AI (2022) and own estimates
* App lifetime at the moment of the 2022 Super Bowl, in months.

during the time period being examined". Google presents the search trends as an index that varies between 0 and 100, reflecting the evolution of the interest in particular names, concepts or keywords over time.

2. Downloads and active users in the US market for each of the apps during the analyzed time period, as reported in Data AI's country breakdown. It is worth mentioning that country level data quality is inferior to the aggregated data quality, since in some cases (related to apps facing legal issues or bans in the US) installs and active users are probably under-reported.

3. Apps' lifetimes (in months) at the moment of the 2022 Super Bowl, since the day they were launched in the app store. Apps' launching dates are also reported by Data AI.

Table 1 presents a set of summary statistics for the chosen indicators across the 39 selected apps.

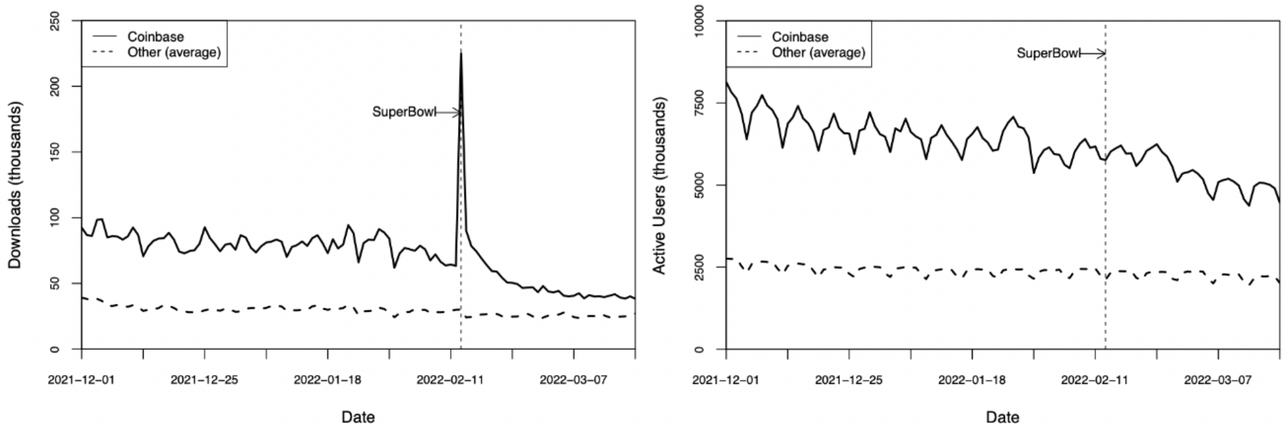
5 Analysis and Results

5.1 Synthetic Control Analysis

Figure 4 displays the trends in downloads and active users for the Coinbase app versus the other crypto exchange apps in the donor pool. As this figure suggests, the average of the rest of the apps would not provide a suitable comparison group for Coinbase to assess the impact of the Super Bowl sign-in bonus campaign on app downloads or active users. During the months preceding the Super Bowl, the levels of the time series in downloads and active users for Coinbase and the rest of the apps in the donor pool had remarkable differences since Coinbase had more downloads and active users in all the pre-intervention period. The trends in both series are relatively parallel until the Super Bowl, and only the downloads series shows a noticeable divergence during that event.

Table 2 shows each donor app's weights in the synthetic control estimation for downloads and active users. The model specification for downloads includes as predictors Google Search trends data, downloads in the US market, app lifetime at the moment of the SuperBowl, and average downloads for three days (Dec 24th, Dec 30th, and Jan 17th). The model for active users includes as predictors, besides Google Search trends data, total downloads, active users in the

Figure 4: Trends in Downloads and Active Users: Coinbase vs Rest of Apps



Source: Data AI (2022) and own estimates

US market, app lifetime and average active users for three days (Dec 24th, Dec 25th, and Jan 18th). As can be seen, the model builds a synthetic Coinbase from a combination of crypto wallets and exchanges very similar to the studied app (such as Binance, Crypto.com, KuCoin and Trust), and regular wallets that allow to buy and sell cryptocurrencies as part of their value proposal (such as Venmo and PayPal).

The synthetic Coinbase that results from these estimated weights is represented in Figure 5, together with Coinbase's real values for downloads and active users, for the period between December 1st, 2021 (two and a half months before the Super Bowl) and March 19th, 2022 (thirty four days after the Super Bowl). For both downloads and active users, it can be seen that synthetic Coinbase resembles the original one during the whole pre-intervention period, thus suggesting that it could provide a good approximation to the counterfactual. We reach to a similar conclusion when we use the estimated weights to compare real and synthetic Coinbase in pre-treatment characteristics (in both downloads and active users models). Table 3 shows that synthetic Coinbase is very similar to the real one in all covariates used in the estimation. By contrast, the simple average of all units in the donor pool would not provide a suitable comparison for Coinbase.

During the Super Bowl and the week after, the downloads series in Figure 5 exhibits a sharp spike that diverges from its synthetic counterpart, indicating a strong positive effect of the Super Bowl campaign on total downloads. This is not the case for the active users series, where the real and the synthetic Coinbase do not show divergences either before or after the Super

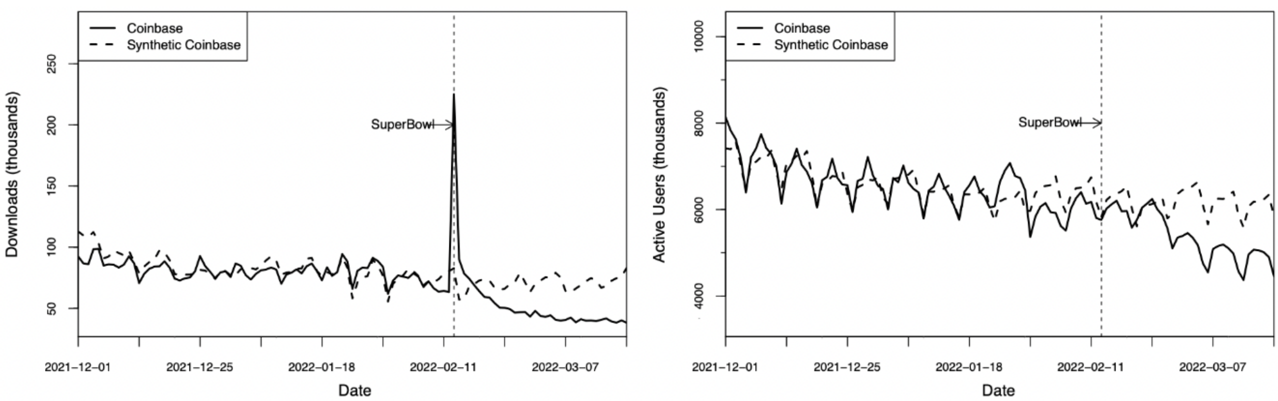
Table 2 - App Weights in Synthetic Coinbase

App	Model	
	Downloads	**Active Users**
Binance	0.154	0.085
Binance.US	0.001	0
BitMart	0.001	0
Bitstamp	0.001	0
Bittrex	0.001	0
Blockchain	0.005	0.132
Blockfi	0.001	0
Bybit	0.001	0
Cash App	0	0.001
CoinDCX	0.002	0
CoinMarketCap.com	0.001	0
CoinSwitch	0.001	0
Cointelegraph	0.001	0
Crypto.com	0.097	0.041
eToro	0.003	0
Exodus	0.001	0
FTX	0.001	0
Gemini	0.001	0
Kraken	0.001	0
KuCoin	0.067	0
Luno	0.002	0
OctaFX	0.002	0
OKX	0.001	0
Paxful	0.001	0
PayPal	0.088	0.13
Phemex	0.001	0
Pionex	0.001	0
Revolut	0.002	0
Robinhood	0.001	0
SoFi	0.001	0
Stash Invest	0.002	0
Trade Republic	0.001	0
Trust	0.007	0.182
Uphold	0.001	0
Venmo	0.541	0.426
Voyager	0.001	0
WazirX	0.001	0
Webull	0.005	0

Source: Data AI (2022) and own estimates (Pre-Treatment Period: Dec. 1st, 2021 - Feb. 12th, 2022)

Bowl, suggesting that the campaign did not affect this indicator.

Figure 5: Trends in Downloads and Active Users: Coinbase vs Synthetic Coinbase



Source: Data AI (2022) and own estimates

Table 3 - Predictor Means before Super Bowl Campaign

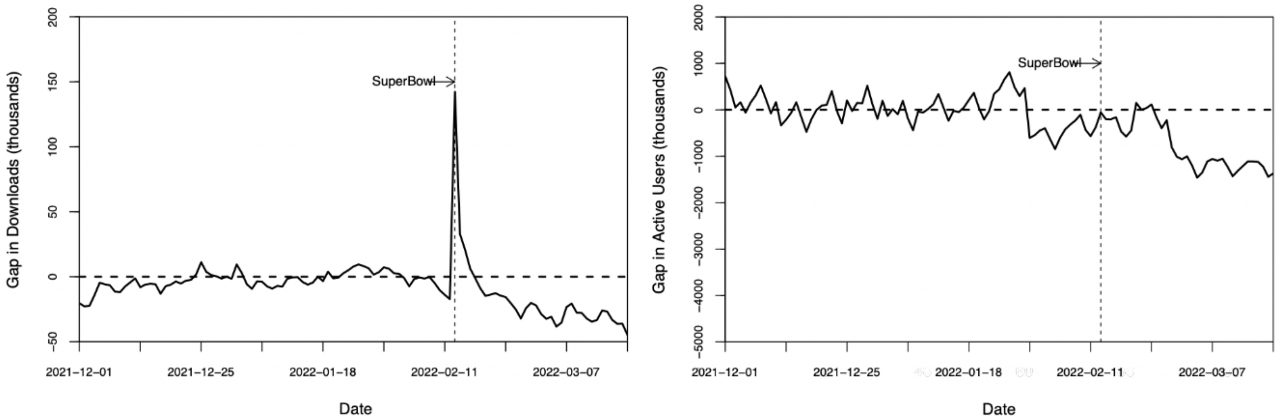
	Coinbase	Synthetic Coinbase	Average Donor Pool
Downloads			
Google Trends (Dec 1st, 2022 - Dec 31st, 2022)	14.31	14.17	3.68
Google Trends (Jan 1st, 2023 - Jan 31st, 2023)	15.00	15.05	3.90
Google Trends (Feb 1st, 2023 - Feb 12nd, 2023)	14.46	14.82	3.97
Downloads US (Dec 1st, 2022 - Dec 31st, 2022)	34,428	37,754	8,614
Downloads US (Jan 1st, 2023 - Jan 31st, 2023)	33,114	30,146	7,241
Downloads US (Feb 1st, 2023 - Feb 12nd, 2023)	33,556	32,651	7,645
App Lifetime (Dec 1st, 2022 - Dec 31st, 2022)	107.00	106.96	54.42
App Lifetime (Jan 1st, 2023 - Jan 31st, 2023)	107.00	106.96	54.42
App Lifetime (Feb 1st, 2023 - Feb 12nd, 2023)	107.00	106.96	54.42
Active Users			
Google Trends (Dec 1st, 2022 - Dec 31st, 2022)	14.31	14.25	3.68
Google Trends (Jan 1st, 2023 - Jan 31st, 2023)	15.00	14.81	3.90
Google Trends (Feb 1st, 2023 - Feb 12nd, 2023)	14.46	15.02	3.97
Downloads (Dec 1st, 2022 - Dec 31st, 2022)	83,329	86,297	31,840
Downloads (Jan 1st, 2023 - Jan 31st, 2023)	80,717	78,546	30,401
Downloads (Feb 1st, 2023 - Feb 12nd, 2023)	71,018	69,056	28,809
Active Users US (Dec 1st, 2022 - Dec 31st, 2022)	3,582,932	3,536,811	795,588
Active Users US (Jan 1st, 2023 - Jan 31st, 2023)	3,306,705	3,230,124	758,335
Active Users US (Feb 1st, 2023 - Feb 12nd, 2023)	3,210,292	3,490,963	801,558
App Lifetime (Dec 1st, 2022 - Dec 31st, 2022)	107.00	106.96	54.42
App Lifetime (Jan 1st, 2023 - Jan 31st, 2023)	107.00	106.96	54.42
App Lifetime (Feb 1st, 2023 - Feb 12nd, 2023)	107.00	106.96	54.42

Source: Data AI (2022) and own estimates

Figure 6 shows the daily gaps in downloads and active users between Coinbase and its synthetic counterpart during the studied period. The impact of the Super Bowl campaign on downloads is substantial, but it doesn't seem to last over time. During the five days after the Super Bowl, the total gap in downloads reaches 210,000 (a 76% increase compared to the counterfactual scenario with no treatment); but after that short period, Coinbase's real downloads begin a downwards trend that results in negative gaps versus the counterfactual scenario. This suggests that the SuperBowl campaign may had only accelerated the app adoption on users that would have downloaded the app anyway (but at a later time period) without being exposed to the campaign.

On the other side, the gaps in the active users series remain unnoticeable until February 26th, thus suggesting no major impact of the campaign on overall user engagement. Since February 26th, a significant negative gap is visible between the real and counterfactual active user series. A direct causal relation between the Super Bowl campaign and this sudden decrease in active users would be difficult to stablish, but such sudden decrease could be associated to another important event of a very different nature. The Russian invasion of Ukraine began on February 24th (Reuters, 2022), and it triggered a set of economic sanctions against Russian (and related or allied countries) individuals and institutions (CNN, 2022). Coinbase was one of the first crypto platforms to support the economic sanctions (Decrypt, 2022) and, as its Chief Legal Officer stated in a post in Coinbase's official blog one week after the invasion started, the platform implemented "geofencing controls to prevent access to the Coinbase website, as well as our products and services, by anyone using an IP address in a sanctioned geography" (Coinbase, 2022). In this way, Coinbase's active users (and even downloads) may have diminished versus other platforms that did not implement any sanctions or whose user base outside the US was insignificant. In any case, no positive effects on Coinbase's active users can be visualized during the month after the Super Bowl campaign.

Figure 6: Gaps between Coinbase and Synthetic Coinbase



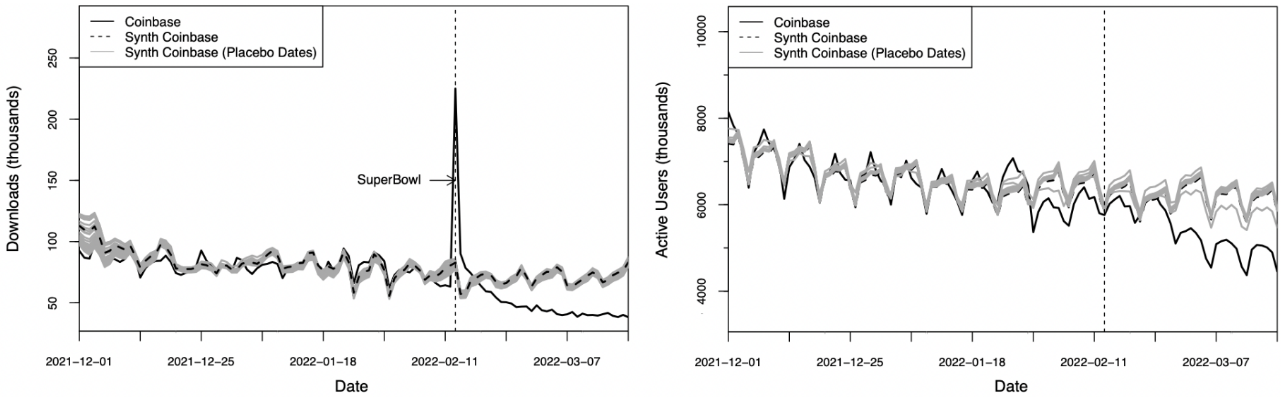
Source: Data AI (2022) and own estimates

5.2 Robustness Checks

In order to further analyze these results, four alternative robustness checks were run. The first check consists of an "in-time placebo" test. The purpose of this test is to establish a fictitious beginning date for the intervention period (a "placebo") in order to determine if there are any apparent treatment effects during the pre-intervention days. The presence of such effects would cast doubts on the true causes of the effects observed during the intervention period. Figure 7 displays the results of applying the synthetic control method to the downloads and active users series for thirty different placebo dates (each day between January 13th, 2022 and February 12th, 2022), together with the synthetic counterfactual estimation presented in the previous section. None of the placebo estimations presents significant divergences versus the real downloads or active users series during the pre-treatment period; and in all cases synthetic Coinbase fits well to real Coinbase (as in the original synthetic estimation).

P-values for this test can be constructed by estimating the probability (if a treatment date is randomly chosen among the placebos) of obtaining, after five days of a placebo starting date of the SuperBowl campaign, a greater or equal effect to the one estimated using the real SuperBowl date. Applying this methodology for each of the series, the obtained p-values are 1/30=0.033 for downloads and 14/30=0.466 for active users, in line with the conclusions from the previous section.

Figure 7: Placebo Campaign Implementation before Super Bowl

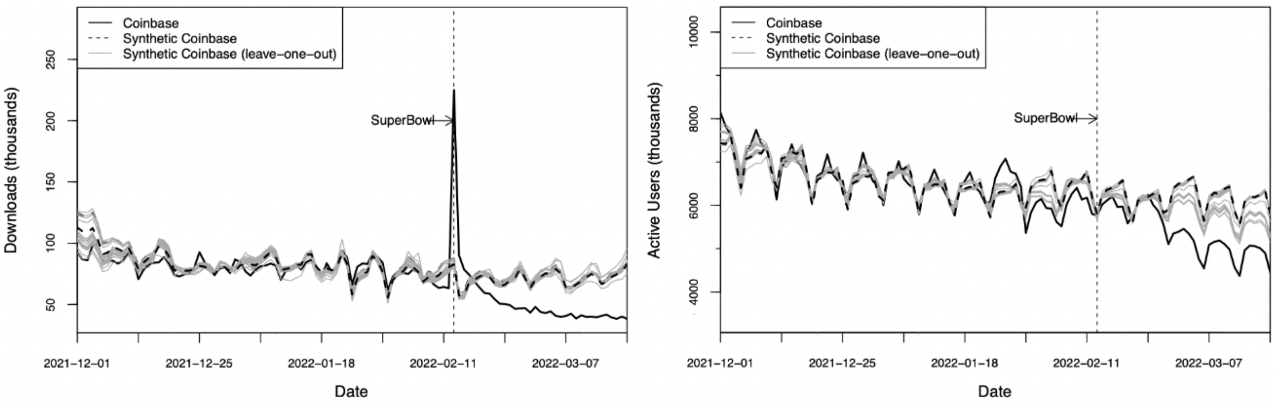


Source: Data AI (2022) and own estimates

The second check is a "leave-one-out" robustness test, where the apps that compose the synthetic control are excluded one by one. This analysis aims to determine if the results are influenced by a single control app, which would indicate that the initial synthetic control (which is made up of 38 apps) may not be a suitable counterfactual. The findings of this analysis are presented in Figure 8. For both downloads and active users, it can be seen that no leave-one-out scenario departs radically from the original model.

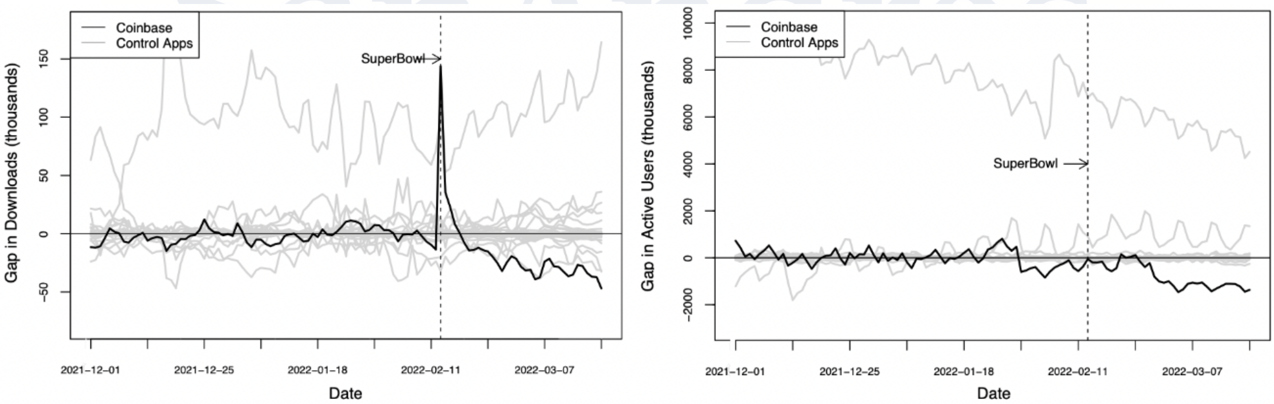
The third check is a permutation test, in which the treatment is reassigned to units that were not exposed to it. This means that the synthetic control method was applied to each of the control apps, moving Coinbase to the pool of donors. If the Super Bowl campaign was the real cause of the spike in Coinbase's downloads, then the estimated impact on Coinbase should be greater than the impact on any other app not affected by the campaign. The results of this test are shown in Figure 9, which presents the differences between each app and its synthetic control for downloads and active users. Analyzing the downloads series, it can be seen that none of the gaps in the 38 control apps resembles the one in Coinbase, thus confirming again the conclusion that the Super Bowl campaign positively affected downloads. Again, this is not the case for active users.

Figure 8: Leave-One-Out Distribution of the synthetic Control for Coinbase



Source: Data AI (2022) and own estimates

Figure 9: Gaps in Downloads and Active Users for Coinbase and Donor Pool Apps



Source: Data AI (2022) and own estimates

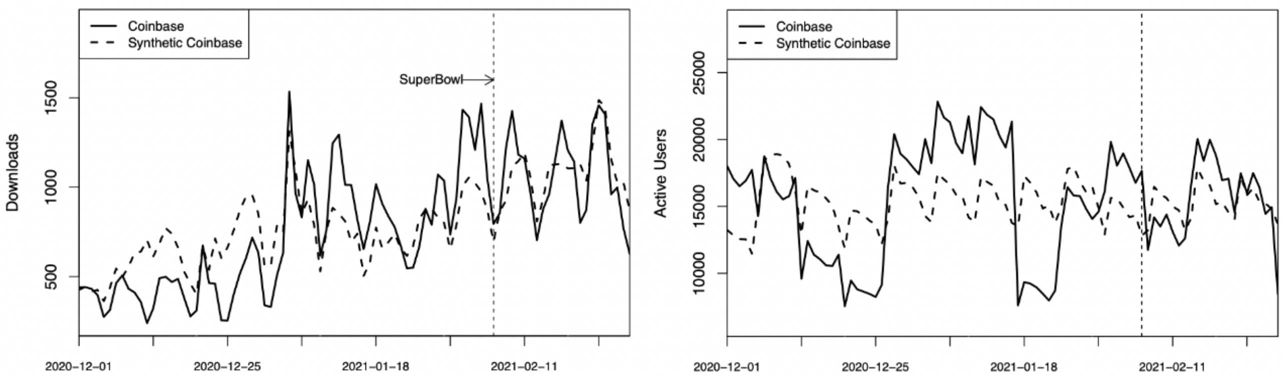
As Abadie et al. (2015) propose, a more precise test can be performed by computing p-values using the proportion of estimated placebo gaps that are larger or equal than the estimated gap for Coinbase. Formally,

$$p - val = Pr(\hat{\tau}^{PL} > \tau_1) = \frac{1}{J+1} \sum_{i=1}^{J+1} I(\hat{\tau}_{iT}^{PL} \geq \tau_{1T})$$

where $\hat{\tau}_{iT}^{PL}$ is the estimated gap for the post-treatment period T when app i is assigned to placebo treatment at the same time as Coinbase. Since Coinbase shows the largest gap in downloads, and for active users only 5 apps show gaps smaller than in Coinbase, the respective p-values are $1/40 = 0.025$ and $35/40 = 0.875$.

The fourth and final robustness check consists of a placebo test using the 2021 Super Bowl [4] as the placebo treatment, since Coinbase did not execute any special marketing campaign nor offered special sign-in bonus during that event. Finding relevant effects from this placebo treatment would indicate that the Super Bowl by itself (and not necessarily the sign-in bonus campaign) may affect Coinbase's app downloads and usage. Figure 10 presents the results of this test. The charts do not suggest any relevant effects, neither on downloads or active users, from the 2021 Super Bowl [5].

Figure 10: Placebo Test Using 2021 Super Bowl



Source: Data AI (2022) and own estimates

[4] The 2021 Super Bowl was disputed between the Tampa Bay Buccaneers and the Kansas City Chiefs on February 7th of that year. The Buccaneers defeated the Chiefs by the score of 31-9.

[5] The quality of the synthetic Coinbase in this exercise is probably inferior to the 2022 Super Bowl exercise, since in this case data is available for only 6 of the 38 donors. Sudden falls in the "Active Users" series may be explained by outages suffered by the Coinbase platform during those months (Nasdaq, 2021).

6 Conclusions

The present study contributes to the literature on digital marketing with a rigorous analysis of the causal effects of a "sign-in bonus" campaign on mobile app usage. Applying a synthetic control approach to the usage of the Coinbase app after the 2022 Super Bowl marketing campaign, we find strong short-term positive effects of the campaign on app downloads, but null or negative effects on active users. These results provide analytical evidence about "sign-in bonus" campaigns affecting user behavior only in the adoption stage (with no significant effect on post-adoption). Several robustness checks confirm the validity of these conclusions.

These findings are particularly relevant since many marketing teams (especially in startup companies) rely on this type of campaigns and assign a large portion of their annual budgets to them. On the other side, business analysts and venture capital funds may create incentives for those strategies since one of the key metrics used to evaluate mobile app companies is the downloads or new users' growth rate. This investigation should raise awareness of the limitations of using those metrics at face value as an indicator of future user activity and profit (the post-adoption stage).

Future research can build upon the present findings in several ways. First, more detailed data on user activity during the post-adoption stage (transactions volume, subscriptions to premium features, revenue, etc.) could be used to better assess the impact of this kind of campaigns. Second, other types of campaigns (with different features and characteristics) could be evaluated using a similar methodology to check how their effect on downloads and active users differ from the sign-in bonus campaigns. Finally, In the case of cryptocurrency-related apps, the effect of the crypto market business cycle (with its booms and busts) on the performance of different marketing campaigns could be assessed.

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