Fire Sales by Funds: the OGX case*

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Abstract

This paper investigates the aftermath of the OGX scandal for investment funds that held OGX stock in their portfolios during the event. Drawing from the fire sales literature, we highlight that when a shock hits an investment fund, investors often rush to redeem their money, forcing fund managers to liquidate assets—typically at a loss—in order to meet redemption demands. Using a synthetic controls approach and publicly available data from Brazil's Securities and Exchange Commission (*Comissão de Valores Mobiliários, CVM*), we demonstrate that the last investors to redeem their funds are not only affected by the initial shock but also suffer additional losses due to the delayed timing of their exits. Our novel approach matches each fund with a synthetic counterpart to simulate its performance had the shock not occurred. Finally, we propose a mechanism for redistributing losses among investors and urge legislators to consider our findings when shaping regulatory frameworks.

Keywords: synthetic controls; investment funds; fire sales; OGX scandal

JEL classification: D18, D47, G10, G12, G21, G24, G28, G51, G53

1 Introduction

When negative information becomes available, efficient market hypothesis predicts that stock prices will react. One of the most common tools that can be used to study this phenomenon is the event study methodology, which consists of testing the significance of abnormal returns observed during a predetermined period after the event (MacKinlay, 1997). This method plays an important role in accessing the relevance of an information, but it is not without limitations. One challenge when using event studies is deciding on the right benchmark that will help to define when a return should be considered abnormal, so we can have a basis for comparison. Recent methods can overcome this problem by using more efficient approaches to create a control group to be compared with the affected unities. Regarding impact, a drop in share value might not be contained within the limits of a single company, causing important damage on the financial market as a whole. This paper is concerned with this second order effect as it investigates how an event involving a public company can be costly for funds shareholders.

Investment funds design portfolio strategies with the objective of maximizing returns. When an exogenous shock impacts a publicly traded company, its effects can propagate to any fund that holds the affected firm in its portfolio. This paper investigates such a scenario, focusing on the repercussions of a specific shock on Brazilian investment funds. Consistent with the findings of Capponi et al. (2020), Capponi et al. (2022), and Jin et al. (2022), our empirical analysis demonstrates that investors who redeem their shares early benefit from a distinct advantage over those who redeem later.

We study the case of OGX, a Brazilian oil company that helped shape the history of the country's stock market. Led by Eike Batista, a charismatic businessman and heir to a rich and politically influential family, OGX planned to compete with Petrobras, the Brazilian oil company founded in 1953 with a majority of its capital held by the government.

In 2010 the company had a valuation of almost BRL 75 billion (approximately USD 45 billion), making OGX the most important company in the group of endeavors created by the entrepreneur (Luzio, 2019). The company's IPO had raised almost BRL 7 billion (around USD

4.3 billion), setting a new record, made more impressive by the fact that it was still a greenfield project. OGX had a rather rapid rise and fall, played a role in the political history of Brazil, and managed to attract some large investors, being an adequate event to be studied.

The date of the event, 15 April 2011, marks the publication by the world-renowned consultancy firm Degolyer and MacNaughton (D&M) of a report that significantly decreased the estimate of the number of oil barrels that OGX could extract from its reserves.

According to Luzio (2019), OGX had several relevant events during its existence. We focus on the publication of D&M's third report because it was arguably one of the most important events, as it confirmed to the market what (at the time) only a few players suspected: that the company was never going to deliver on its promises. In this context, we also chose to employ a different method, other than the traditional event study, as we wish to demonstrate the profound effect caused by the release of D&M's report. Typically, event study techniques are used to portray the effect of an event in a short-term horizon, using some measure of abnormal return chosen by the researcher. In our case, Degoyler and MacNaughton revealed to the market that the mission of OGX could never be fulfilled.

To demonstrate the long-standing impact that the event had on some of the funds that carried stocks from OGX we use the synthetic control methodology of Abadie brazileand Gardeazabal (2003). Typically used for assessing public policy effectiveness, this method tries to illustrate how a given unit would've behaved if it hadn't received a specific treatment. Unlike an event study method, synthetic control finds a control group for each unity, which allows us to compare the decreasing performance of funds that had OGX with a control grouped that was optimally selected using the method. In addition, the decision to include the OGX stock in a fund portfolio is not random, making it difficult to analyze the performance of the fund. Abadie brazileand Gardeazabal (2003)'s method tries to mitigate this problem by creating a synthetic control, a combination of all units that did not receive the treatment in question, combined in such a way as to mimic certain observable characteristics of the treated unit. The basic idea is that the synthetic control would serve as a counter-factual, a control group that is similar to the treated unit except for the fact that it did not receive said treatment. In the context of our work, applying this technique means finding, for each fund affected by the

event, a synthetic untreated counterpart, in order to understand its performance and behavior after the fact. We create a synthetic fund using characteristics from the treated fund, so that we can build a unity that serves as the best candidate for a proxy of the treated fund. Ideally, the only difference between actual and synthetic funds should be the occurrence of treatment. To our knowledge, one of the strengths of the paper is being the first to use synthetic controls to approach this problem.

After identifying the affected funds, we can illustrate how their performance deviated from the path suggested by the synthetic control and the advantage that some investors get from deciding to redeem their money ahead of others. As explained in Jin et al. (2022), when an investor calls to withdraw her money, funds use the price of the day's share to calculate the amount due, without taking into account the costs that will arise in the next days from this transaction. To mitigate this imbalance, some countries suggest implementing what is called swing pricing. Instead of absorbing the costs internally, the fund should apply a variable share price to transfer some of the costs to redeemers. Our evidence advocates that swing pricing should also be adopted in Brazil.

To give our results more meaning, we use a placebo test treating the control funds as if they had OGX stock at the of the event to see if their returns behaves similar as the ones observed for the real treated group. Through this method, we identify 85 funds that never recovered from the event, with some even canceling their registration in the years that followed the shock. Furthermore, examining the characteristics of these funds, we find that funds with more shareholders and whose portfolio concentrated in stock investments were particularly impacted by the release of the third D& M report.

The rest of the paper is organized as follows: section 2 brings the literature closely related to our problem; section 3 explains the methodology used; section 4 discusses our results; and section 5 presents the results obtained using synthetic control; 5.1 presents a placebo test and the characterization of funds affected by the event; and, 6 concludes.

2 Literature Review

Funds have been around for hundreds of years (Elton brazileand Gruber, 2013). From perception an investor, they represent an attractive mechanism, mainly for 2 reasons: (i) first, pooling resources from multiple investors can allow fund managers to pursue better investment opportunities while sharing the costs; (ii) second, the fund manager has more time and incentives to monitor the portfolio and to optimize asset allocation. Even in countries like Brazil, where the fund industry started only during the late 1960s, funds are becoming increasingly popular.

As a research object, funds originate multiple interesting questions. A strand of the literature seeks to understand the determinants of fund performance. Among the factors that affect performance, Detzler (1999) shows that expenses are negatively related to the return of the US bond fund. This is somewhat counter intuitive, since a relevant share of expenses comes from rewarding the funds managers for their performance. In a cross-country study, Ferreira et al. (2013) add liquidity of financial markets, the strength of a nation's institutions, fund size, fund age, and fund flow as important determinants for a fund's performance.

The relationship between a fund's flow and its performance is well established in the literature, even in countries other than the US (Ferreira et al., 2012; Berk brazileand Green, 2004). The fund's past performance can help explain future flow, and, in the context of trying to understand how this relationship works, it becomes relevant to examine how these institutions react when returns are below a certain level. A second strand of literature focuses on understanding the behavior of managers and investors when funds start to under-perform.

When funds start presenting losses, shareholders become concerned with preserving their wealth, and so make a run for their money, withdrawing resources from the distressed funds. Depending on the amount redeemed, fund managers are forced to abandon their strategy and sell assets in their portfolio to make payments. Since funds tend to have low cash buffers, the need to sell assets can arise even with few redemptions.

The so-called fire sales can exert pressure on prices as shown, for example, in Coval brazileand Stafford (2007) and Ellul et al. (2011). In their urge for liquidity, managers tend to

accept a lower price than they usually would. Other funds not suffering from withdrawals, but holding the same security as the ones selling, also suffer as they see a decline in value in their portfolio. In other words, fire sales create externalities and therefore affect those not directly involved in fire sales type transactions (Chernenko brazileand Sunderam, 2020).

On the other hand, Dyakov brazileand Verbeek (2013) theorize that qualified investors can take advantage of this transitory deviation from fundamentals and short-sell assets to gain when prices drop. This opportunity for gain can further aggravate the situation of funds in distress. The implementation of a short-selling strategy can make the pressure on prices last longer, creating a negative-feedback spiral making way for other investors within the fund to execute front-running strategies. As Dyakov brazileand Verbeek (2013) argue, short-sellers seeking to take advantage of a fire sales scenario can distress the entire market, creating a liquidity crisis.

Another problem with fire sales is that it creates a vicious circle. The decrease in the price of the fund shares leads to further withdrawals that, in turn, create additional fire sales (Shleifer brazileand Vishny, 2011). Shareholders who take longer to redeem are in a disadvantage compared to those who are quick to take their money out. In a way, investors who take longer to withdraw their money are forced to absorb the costs left by the other investors who were quicker to leave.

For the reasons mentioned, fire sales pose a problem for legislators. To break the problematic pattern, funds should use a variable share price, or swing price, to make the investor pay for the cost associated with the redemption. According to Capponi et al. (2020), in order for the swing pricing to be effective, funds should apply a different price for each transaction, instead of determining a fixed adjustment to be used with every investor.

Outside of academia, the Securities and Exchange Commission (SEC) in the US announced Rule 22c-1 in 2016, which allowed open-end funds to use swing pricing in their redemption calls. Even before, other countries such as the UK, France, Switzer, and Germany have long since adopted swing pricing (Capponi et al., 2022). Empirical evidence with respect to UK data shows that the measure has been effective in ending the first mover advantage (Jin et al., 2022).

As in other areas of research, we do not see enough evidence that originates from developing economies. We offer to mitigate this gap by bringing data from funds operating in Brazil.

3 Empirical Strategy

The rationale for employing the synthetic control method to identify the effect of the OGXP3 stock drop on investment funds—specifically around the event date of April 15th, 2011—is to construct a synthetic fund from a pool of funds that did not hold OGXP3 at the time. This synthetic fund serves as a counterfactual and is designed to closely mirror the characteristics of the treated fund, i.e., a fund that held OGXP3 in its portfolio during the event. The primary criterion for similarity is the return profile of the fund. To better illustrate this comparison, we utilize cumulative returns as our main performance metric, represented by:

$$Y_{it} = \frac{R_{it} - R_{i(0)}}{100}$$

For each fund i we subtract the return at time t from the first return of the series and divide the result by 100. Following Abadie et al. (2010)'s method, we wish to estimate the difference between the return from the treated *versus* the untreated unity. In other words, we wish to find: $\alpha_{1t} = Y^I_{1t} - Y^N_{1t}$, or the difference between the treated unity after the event and the behavior of the same unity, if it hadn't receive the treatment. Naturally, we can't observe Y^N_{1t}.

Using the formal notation provided in Abadie (2021), we have a vector of units (in our case funds) $J+1$, and a vector of weights, given by $W = (w_2, ..., w_{J+1})'$, so that the synthetic control estimator of Y^N_{1t} is given by:

$$\hat{Y}^N_{1t} = \sum_{j=2}^{J+1} w_j Y_{jt}$$

Synthetic control can be understood as a generalization of differences-in-differences, as we can control for unobserved factors that affect all of the funds and that vary through out time. The

equation we estimate is represented by:

$$Y_{it}^{N} = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \epsilon_{it}$$

Our predictors are represented by Z; the vector of observable time-variant variables is given by μ; and the common factor to all unity is given in δ. As Abadie et al. (2010) explain, searching for a fund to serve as a comparison to our treated fund is, in reality, an optimization problem, where we wish to find a weight vector that attends the following optimization condition:

$$\arg\min_{V \in \mathcal{V}} (Z_1 - Z_0 W^*(V))'(Z_1 - Z_0 W^*(V))$$

Where V is a $k \times k$ positive semi-definite matrix chosen to minimize the quadratic error in our estimation procedure. Z_0 denotes the vector of pre-treatment characteristics for the control group, while Z_1 represents the corresponding vector for the treated fund. The vector W contains the weights assigned to each unit in the control group and is determined to best approximate the characteristics of the treated fund.

We use the classic implementation by Abadie brazileand Gardeazabal (2003), which restricts the weights to $[0, 1]$ to avoid extrapolation. Returns are explained by a group of variables called predictors. The chosen predictors for the funds returns are the 4 (four) largest stock positions in their portfolio, scaled by the fund's equity. Each variable is described in Table 1:

We use this model because (i) we consider two funds to be similar if they present a similar return at a given period of time and, (ii) because a large part of a funds' return can be explained by the behavior of the assets in which it has the largest stake relative to size (given by the funds' equity). As explained by Abadie (2021), "the credibility of a synthetic control estimator depends on its ability to track the trajectory of the outcome variable for the treated unit for an extended preintervention period", thus justifying our choice of predictor variables. The relationship estimated using synthetic controls is given by:

$$Y_{it} = w_j max\_one_{it} + w_j max\_two_{it} + w_j max\_three_{it} + w_j max\_four_{it} + w_j max\_five_{it}$$

Table 1: Predictors used to explain return.

Predictor Name	**Description**
max_one	Largest stock position of the i-th fund, in Brazilian *Reais*, at month t. This number divided by the fund's equity value at month t.
max_two	Second largest stock position of the i-th fund, in Brazilian *Reais*, at month t. This number divided by the fund's equity value at month t.
max_three	Third largest stock position of the i-th fund, in Brazilian *Reais*, at month t. This number divided by the fund's equity value at month t.
max_four	Fourth largest stock position of the i-th fund, in Brazilian *Reais*, at month t. This number divided by the fund's equity value at month t.
max_five	Fifth largest stock position of the i-th fund, in Brazilian *Reais*, at month t. This number divided by the fund's equity value at month t.

w_j represents the weights that will be adjusted to find the best controls for each fund.

Even though the event date is unique, the difficulty (and novelty) of using synthetic control in our problem is that unlike the tobacco policy problem (Abadie et al., 2010), or the Basque country case Abadie brazileand Gardeazabal (2003), each fund has a large pool to be examined in order to find a synthetic candidate. As in Abadie brazileand Vives-i Bastida (2022), this situation can lead to overfitting and bias, but since our horizon is only of a few months, some of this bias is mitigated. Another concern is that each fund begins at a different point in time, which means some funds that carried OGXP3 at the time of the event were operating only for

a few months. Having insufficient data points before the event date can also prejudice our estimation.

4 Data

In Brazil, Instruction 555 issued by the country's Securities and Exchange Commission (*Comissão de Valores Mobiliários*, or *CVM*) forces funds to share their portfolio with a delay of up to 90 days, to preserve the manager's strategy. More recently, Instruction 184 allowed the delay period to extend up to 180 days. Since we focus on data published before the new rule, our database suffers from a 90-day lag, at most. All fund information is publicly available on the CVM website[1].

For each month, starting in 2005, we have the list of assets (stocks, government bonds, investments overseas, swaps, etc.) in the fund's portfolio. The amount invested in that asset, along with the monetary increase (decrease) in the fund's position on that given month.

A second set of data extracted from the same website [2] gives us the equity of the funds, the price of the shares and the number of shareholders on a daily basis.

Lastly, another group of data allowed us to form a database with qualitative information about the fund. Whether or not the fund is open end; if it is exclusive; and the fund's class. Some funds changed characteristics during the period examined, but our database provides the date and content of the change.

Dealing with different sets of data forces us to define criteria to merge the databases together. We chose to join the databases using the funds national register number (*Cadastro Nacional de Pessoa Jurídica*, or *CNPJ*) and the date. When necessary, we aggregated the data at the month level, which is the frequency funds have to report their portfolio.

After merging the databases and filtering for funds that had OGX stock in their portfolio at the time of the event, we start with a base of 878 funds and information starting from Janurary, 2005.

[1]The data is updated frequently and can be found by accessing: https://dados.cvm.gov.br/dataset/fi-doc-cda.
[2]Daily information on funds can be accessed on the address: https://dados.cvm.gov.br/dataset/fi-doc-inf_diario.

5 Results

As described, the funds' portfolios are reported on a monthly basis. We take the portfolio on 30 April 2011 and filter all funds with OGXP3. This resulted in 878 funds. In this subset, some funds sold their position before the event, while others bet against OGX. After filtering out these cases, we proceeded to run the synth test. Using R, we tried to find a synthetic match for each remaining fund to observe how the event affected the return. Not every fund had a perfect synthetic match and, therefore, had to be excluded.

The package for conducting synthetic tests in R imposes certain restrictions on our database. We must ensure an equal number of columns for both treated and control variables (that is, the number of predictors for each group should be identical). To meet this requirement, we excluded funds that did not meet the following criteria: (i) both treated and control funds must share the same start and end dates, with no gaps in between, and; (ii) funds must have precisely the same number of predictors. The necessity of using a squared matrix resulted in a significant loss of data. In the end, out of 878 treated funds, we were able to successfully run the synthetic control for 510 funds.

With those results in hand, we then encountered the challenge of examining each synthetic and treated pair while attempting to perform inference work. As explained didactically by Alves (2022), especially in cases involving long periods of time or a large number of units to compose our synthetic fund, we may end up with an over-fitted model. One approach to analyzing the results could involve a visual form of inference, by inspecting each plot of the treated and synthetic funds to select those which exhibit an ideal curve, that is, a similar pattern between treated and synthetic units before the event, followed by a distancing, yet somewhat parallel behavior after the event occurs. As an example, Figure 1 displays one of the results of our study and the type of pattern we hope to observe in each synthetic control test we conducted.

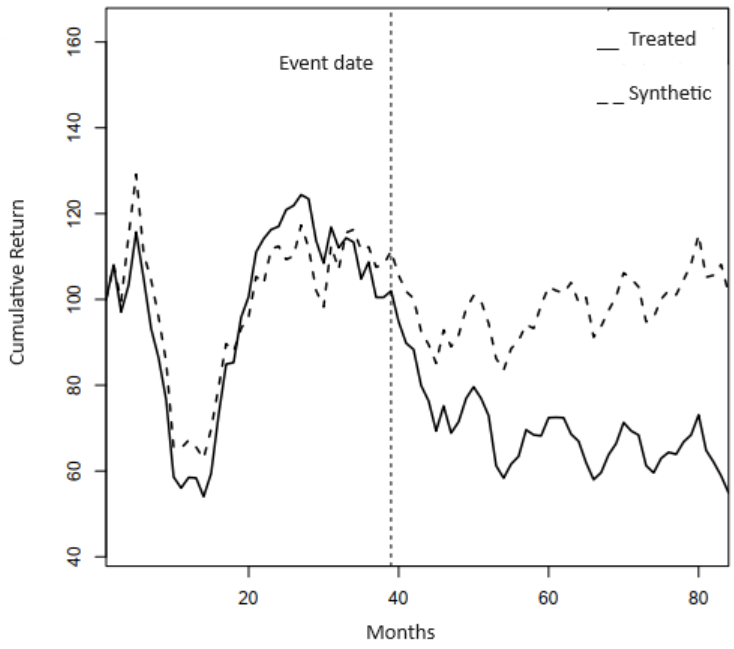


Figure 1: Results example

Based solely on visual screening, we select 85 funds that were shown to be affected by the publication of the third D&M and displayed a desirable fit (thus discarding 425 graphs that did not show an adequate fit), using only the graphs of the treated fund and its synthetic counterpart as a criterion. Next, we learn more about these 85 funds. Using another database extracted from *CVM's* portal we identified the main characteristics of each fund.

As shown in Table 2, the majority (65 out of 85) of the affected funds are stock funds, a type of fund that is required to invest at least 67% of its equity in (i) stocks, (ii) shares of other stock funds, and (iii) subscription rights. These funds have stock prices as their main risk factor. A smaller share of funds are classified by the Brazilian law as multi-market funds, a type of fund that does not concentrate its investments in any particular type of asset, holding a diversified portfolio attached to multiple risk factors.

Table 2 also shows that 31 (36%) funds are classified as exclusive funds, a specially tailored fund made to hold the investments of a single shareholder, as defined by CVM's Instruction 555. We exclude these funds because the main goal of our paper is to discuss how investors who take longer to redeem their money face more harm during a crisis in a fund, when compared to

the so-called first-movers. As a result, we end up with 54 funds affected by the publication of the third D&M after applying the strict criteria demanded by R's *synth* package and removing funds with single investors.

Table 2: Characteristics of the affected mutual funds

Fund type	**Not Exclusive**	**Exclusive**	**Total**
Stock Funds	46	22	68
Multi Market	8	9	17
Total	54	31	85

We have 54 nonexclusive funds affected by the release of the third D&M report. The results of our synth test can be seen in Figures 3 and 4, where we have a graph for each fund. Each plot has a vertical line to mark the moment the event took place.

We can see that the distance between the actual fund's cumulative return and the synthetic fund's return widens throughout time, indicating that the loss for later redeemers, that is, investors who take longer to withdraw their money, is actually greater than the loss faced by investors who take out earlier.

Compiling all results into a grid, as shown in Figures 3 and 4, we can see that the advantage of early redeemers exists for the total of 54 funds in our set of results. As the distance between the synthetic fund (traced line) and the actual fund (continuous line) widens, we see that investors who redraw first can mitigate their damages, when compared to investors who take longer to redeem.

In order to end the first-mover advantage observed in Brazilian funds in times of crisis, we suggest *CVM* allow funds to implement a swing price, forcing investors to redraw at a different price other than the share price observed for that particular day. So-called late redeemers are left with the costs associated with the fire sales managers having to do in order to make the payments to the first investors in line to call out for their money. This imbalance can lead to further redraws and fire sales that put additional stress on the financial market as a whole. However, swing pricing should allow for not only a more equitable treatment of investors but also the containment of crises when a company faces distresses that spread out into other players of the financial industry.

For practical reasons, we divide our results into Figures 3 and 4. The funds are shown in no particular order.

Figure 3: Each plot represents a pair treated (continuous line) and synthetic (traced line) fund found when we conducted the multiple synthetic control tests. The vertical line marks the event occurrence.

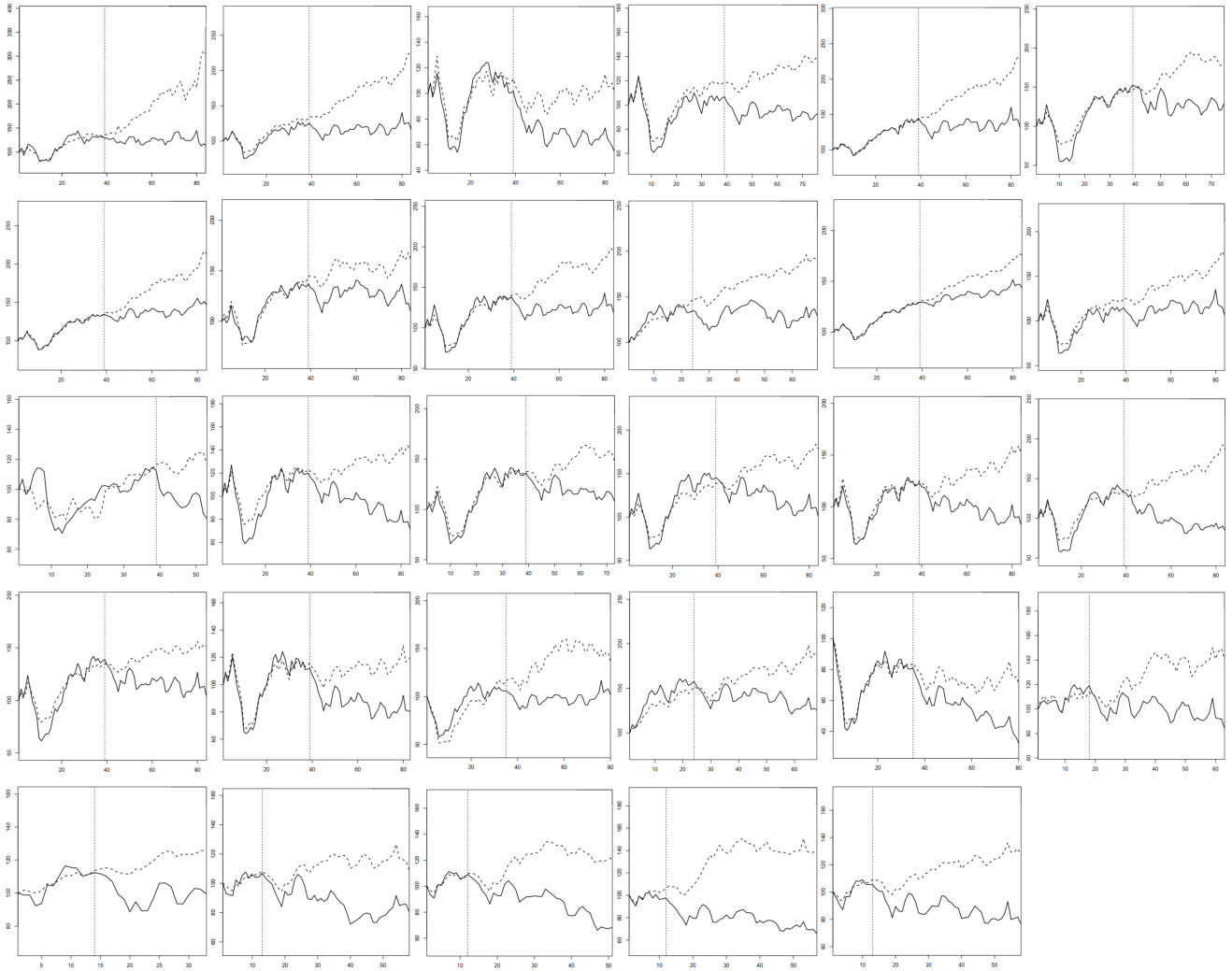
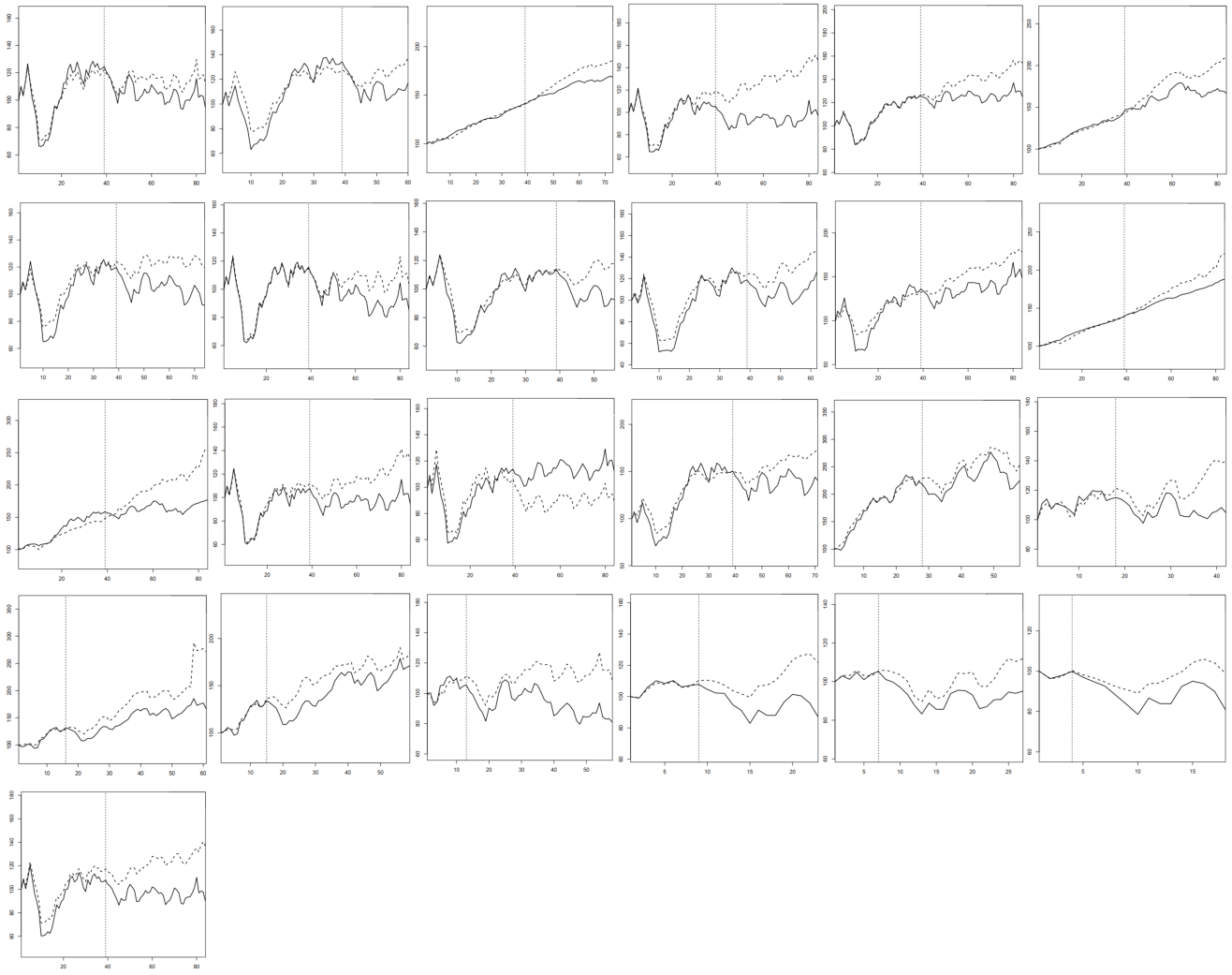


Figure 4: Each plot represents a pair treated (continuous line) and synthetic (traced line) fund found when we conducted the multiple synthetic control tests. The vertical line marks the event occurrence.



Relying solely on visual criteria to select the best fits is not the most rigorous scientific approach, as it introduces inherent bias associated with the individual interpreting the images. Even two researchers with similar backgrounds could potentially select different sets of results.

Another issue with using a visual form of analysis is that we lack a quantitative measure of the impact some funds suffered after the publication of the third D&M. To address this limitation, we can perform placebo tests to determine if the effects are as significant as those observed during the initial set of synthetic tests.

A placebo test means that we take each fund from the control group and simulate as if this unit were actually treated. We then run the synthetic control test and compare the results with those obtained in the original test (with real treated units). This type of statistical test is known as Fisher's exact test and is discussed in Section 5.1.

5.1 Fisher's exact test

To solve our problem of showing the impact of the OGX event, we could apply differences-in-differences estimation, but with thousands of funds to analyze, we are still left with the problem of finding funds that are similar to each other, according to our definition of similarity. Part of this problem is taken care by using Abadie brazileand Gardeazabal (2003)'s synthetic control, but we still need to find an appropriate scientific method to analyze the output. In our previous discussion, we explain that visual selection is not an adequate method as it is prone to bias associated with the individual selecting the best graphs. We could, instead, apply event study methods, but these techniques do not allow us to compare our results relative to unities in a control group. One of the advantages of using synthetic control is that we can compare the performance of the affected funds with the performance of our synthetic funds.

Instead of solely relying on visual inference of more than 500 graphs, we sought to supplement our analysis with a placebo test, following the methodology outlined by Cunningham (2021) and Abadie et al. (2015). Specifically, we implemented Fisher's Exact Test in a step-by-step manner, simulating the scenario where each fund in our control group received the treatment (i.e., held OGX stock at the time of the event).

In April 2011, we identified 2,105 funds that did not include OGX stock in their portfolios. In the initial stage, we performed a synthetic control test for each of these funds. Subsequently, we selected a post-treatment period to assess the impact of the intervention, comparing the cumulative return of each fund with its synthetic counterpart. If the synthetic test is fitted correctly, the distance between the treated fund and the synthetic fund widens after the event. This means that we need to choose a period that is distant enough from the event, so we can compare the impact suffered by the treated funds and the placebo funds. That said, we focus on the impact 10, 15 and 20 months after the event. If the inclusion of OGX stock influenced the future performance of certain funds, we anticipated observing a larger difference between the observed and synthetic returns for funds in the treated group compared to those in the control group. To assess this, we computed $Y_t - Y_t^*$ (the difference between the cumulative return observed for the treated unit and the calculated cumulative return of the synthetic fund) after ten, fifteen, and twenty months after the event for each treated fund and compared this result with the same measure calculated for the control group. This approach enabled us to derive a metric for the significance of the results pertaining to the treated funds.

Pretending that the control funds were affected by the event gives us the opportunity to compare the impact provoked by the publication of the report. Concentrating exclusively on funds that carried OGX stock at the time of the event makes it difficult to evaluate whether the impact, or the loss in return observed after the event, was relevant or not. To compute the significance of the impact achieved by each treated fund, we tallied the number of placebo funds that exhibited an impact equal to or greater than the value observed for the treated fund. Subsequently, we divide this count by the total number of funds (placebos plus treated). This gave us an idea of the statistical significance of the results we obtained for each affected fund.

After calculating the difference between the cumulative returns for the treated and synthetic groups, we used a measure for the statistical significance of each result. Finally, we consider the impacts of funds with a calculated statistical significance of 5% or less. Our results are presented in Table 3.

Impact of the event			
Statistics	Impact on Return 10 months after	Impact on Return 15 months after	Impact on Return 20 months after
Mean	-49.60	-53.05	-53.26
Median	-45.59	-51.02	-51.95
Max.	-34.98	-39.20	-36.27
Min.	-81.66	-81.17	-88.30
SD	13.31	10.40	13.87
Total significant funds	48	67	85
Total funds	446	413	374
Shareholder Impact	-3,662	-4,746	-5,878

Table 3: We focus on the impact suffered by the funds at three time points after the event: 10 months, 15 months, and 20 months since the shock. Afterward, we calculate the summary statistics for the funds that show a calculated impact with statistical significance of 5% or less. Starting from the first row, we provide the mean, median, minimum, maximum, and standard deviation values concerning the impact on the return measured for each fund. *Shareholder Impact* gives the number of shareholders that exited the funds relative to the date of the event. Total funds is the sum of the treated fund under analysis plus the placebo funds. Total significant funds is the total of treated funds whose impact after the event had shown a statistical significance of 5% or less.

In Table 3, we present the descriptive statistics of the calculated difference between the cumulative returns for the treated and untreated funds. Although significance varies (5% or less), on average, the funds observed a decrease of 50% in their return one month after the event. Even 20 months later, they still experienced a loss of 53% in return. Given this economic significance, we can expect investors in these funds to redeem their shares, initiating a vicious circle that could harm subsequent redeemers. In fact, upon examining the daily reports that funds are required to submit to the CVM, we found that some funds had nearly 22% fewer investors 10 months after the event, resulting in a 42% loss 20 months later. Among the 99 unique funds, almost 5,900 investors had left these institutions 20 months after the event.

We characterize the 99 unique funds using the CVM register database. Most (67%) of these funds canceled their registration at some point after the event and therefore are no longer operating. In addition, nearly all are non-exclusive funds. In terms of their classification, 65 (66%) are stock funds, as required by law to have at least two thirds of their portfolio composed

of stocks. The remaining funds are classified as multi-market funds, investing in a diversified portfolio that does not focus on specific assets.

Within the most affected funds, we find diversity in their characteristics with regard to the number of shareholders they hold, the number of days until a shareholder receives his money after calling to redeem his investments, and the type of portfolio these funds build. It is natural to inquire if any of these characteristics contributed to the observed performance the funds had since the event. To further investigate this, we ran a cross-sectional linear model with all funds with available data from CVM. Using the variables in Table 4 we ran the especification described in (1) relating the cumulative return since the event to the characteristics of each fund:

$$\text{cumulative\_return}_i = \beta_1 dummy\_multimarket_i + \beta_2 dummy\_seven_i + \beta_3 days\_to\_redeem_i + \epsilon_i \quad (1)$$

We expect multimarket funds to better handle themselves during a crisis, since they are more diversified than stock funds. Therefore, we expect the relationship between return and the multimarket dummy to be positive. As for the day-to-redeem variable, we also expect a positive relationship with the return, since the fund manager does not have to hurry to sell assets once shareholders redeem their investments. On the other hand, we predict a negative relationship between return and the dummy variable that marks funds with more than seven shareholders. This number was chosen based on the descriptive statistics of the funds that showed that the median number of shareholders in our sample is 7 (see Table 5). We expect funds with fewer shareholders to be better monitored and have more sophisticated investors.

Our sample was built with all funds that existed at the time of the event and that we were able to match to the data base with the characteristics of each fund from CVM. This included 82 of the funds most affected by the event. Because the CVM data base did not have information on funds that had canceled their registration, we collected information on those funds by hand, reading through their regulation. After that, we excluded funds that had only one investor at the time of the event, resulting in a sample of 47 of the most affected funds plus 1,971 that

Variable	Description
cumulative_return	Cumulative return starting from the day of the event.
dummy_multimarket	Assumes 1 if the fund is a multimarket fund.
dummy_seven	Assumes 1 if the fund has more than 7 shareholders one week before the event.
days_to_redem	Days until the shareholder receives the money from the redemption divided by 252, which is the number of working days in a year.

Table 4: as table 5 shows the median of shareholders is 7. This is why we created a dummy to separate funds with few shareholders.

existed around the time of the event. Table 5 shows the descriptive statistics of the fund sample used to test our model.

Table 5: Descriptive Statistics.

Statistic	N	Mean	Median	St. Dev.	Min	Max
Cumulative_return	2,018	15.5	18.29	25.3	−65.0	785.4
Days_to_redeem	2,018	0.0280	0.003968	0.08378	0	1.079
Total shareholders	2,018	2,465.1	7	30,411	2	805,158

The results of our cross-sectional regression are presented in Table 6:

Table 6: Results from the cross-section regression ran using Model 1.

	Dependent variable:
	cummulative_return
dummy_multimarket	15.378**
	(7.565)
dummy_seven	−7.745***
	(1.123)
days_to_redeem	19.737***
	(6.701)
Constant	3.420
	(7.575)
Observations	2,018
R^2	0.027
Adjusted R^2	0.026
Residual Std. Error	25.013 (df = 2014)
F Statistic	18.940*** (df = 3; 2014)
Note:	*p<0.1; **p<0.05; ***p<0.01

As seen in Table 6, all variables presented statistical significance. The variable that measures the number of days that investors have to wait until their redemption requests are concluded showed a significance of 1%, a reasonable result since funds with longer redemption periods do not have to rush to sell an asset once an investor asks to leave the fund. Another result shows multimarket funds are associated with higher returns (15%). Since these funds have more freedom to decide their investments and do not have to concentrate their portfolio with stocks, they are better at compensating for negative results through diversification. Lastly, as predicted, funds with more than 7 shareholders tend to have lower returns. As mentioned, funds that concentrate fewer shareholders tend to hold more sophisticated investors who will closely monitor the fund and push for different strategies once the fund starts to underperform.

If we focus on the funds most affected by the event in our sample with the characteristics of each fund, we find the lower quartile, or the 25% funds that performed worse since the event, also holds the funds with a median of 150 shareholders and with the majority of them being stock funds.

In general, the publication of the third D&M was highly detrimental to some funds that held OGX in their portfolio, resulting in a significant value loss and harm to investors. Our findings underscore the need to implement protective mechanisms to protect funds' shareholders following significant negative events. As a first approach to our problem, we decided not to limit our analysis by excluding funds (except those with only one investor) from our sample. However, the diversity of funds populating the Brazilian industry demands we be more careful to compose our sample. For example, if we include funds that had options in OGX, we would have different funds in our sample. This could translate into different evidence for our problem.

Another limitation in our study is that it can not by itself justify the need for swing pricing ruling. Additional studies are necessary to shed a light on how investors and funds behave during moments of distress. Before implementing a new rule (such as swing pricing), researchers and regulators should study what would be the best mechanism in the interest of the market as a whole.

6 Concluding remarks

Around 2011, famous Eike Batista's company OGX was facing trouble as consulting company Degolyer and MacNaughton released their report stating OGX's future oil extraction volume was, in fact, much lower than previously announced by the company. We analyzed more than 800 funds in Brazil that had OGX stock in their portfolio and found a method to display how some of these funds were irreversibly affected by the price drop in OGX's shares. Using Abadie brazileand Gardeazabal (2003)'s synthetic control, we show evidence of first-mover advantage in Brazilian funds industry.

Due to their nature, funds tend to have small cash reserves. When hit by a crisis, these funds have to deal with unforeseen redraws by investors. Their response is to sell the assets in their portfolio, usually at a loss, so they can meet the demand of the investors. Consistent with Jin et al. (2022) and other works in the literature, this paper empirically demonstrates that, in times of crisis, when funds' shareholders run to redraw money from funds, the first investors to redeem have an advantage against the last redeemers.

The funds that were shown to be affected by the event in OGX had an irreversible drop in their return. Synthetic control allowed for a visualization of this loss, while also showing how the last investors to ask the fund for their money back are forced to accept a lower share price than the investor who was quicker to redeem.

The fact that later redeemers accumulate a greater loss than first movers suggests that *CVM* should seek to implement regulation, such as a swing pricing rule, in order to allow funds to apply a variable share price once they are forced to liquidate assets to meet redemption in times of crises. This policy could end the disadvantage of later redeemers while also helping to limit the damages brought by a crisis in a particular company.

Even if our evidences suggest the need for regulators to protect a group of investors, further studies are necessary to help us to better understand how the funds behave during moments of distress.

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