Technological disasters and stock returns: a causal study of the mining disasters in Brazil.

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Preliminary Version: Do not cite nor quote.

June, 2019

1 Introduction

Financial markets are considered the closest example on what would be a frictionless market due to its capacity to adjust prices, incorporate new information, low barriers to new investors, among other characteristics (NETO, 2009). There is a vast literature on the determinants of stock prices, in which it is disclosed that the value of a certain stock option will be a function of the company indicators, including profits, capital, revenues, in other words, the price depends on the assets and liabilities of a given company because they are, in essence, a price for a part of the firm.

However, there are other factors that could drive the decisions of buying and selling of investors, depending on their expectations regarding the future. Expectations are influenced by the company balance sheets but also by the market and the economy in general. Moreover, if there is a shock either in the economy or the firm, this could lead the investors to buy more or less stocks. Kaplanski & Levy (2010) investigate the role of aviation disasters and stock prices and their analysis showed that a plane crash can have significant bad effects on the prices paid for the aviation company depending on the severity of the accident. Barro (2009) studied, in a general equilibrium framework, the impact of disasters in the economy as a whole and concluded that risk aversion makes investors to overcompensate for the disasters, shrinking the GDP and contracting the economy. Prices are also propense to terrorist attacks, as Brounen & Derwall (2010) study suggests. But what about technological disasters where the company may be responsible for the event?

In November of 2015 a dam broke in the vicinity of Mariana municipality, located in the Brazilian state of Minas Gerais. This was considered the worst environmental disaster of the Country. Shortly after the disaster, the company already registered losses of more than $ 3 Billions in its market value (G1, 2015), but this came after a very bad year for

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Field paper for the Strategy in Finances course of the Undergraduate program in economics from ESAG/UDESC.

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Key-words: Synthetic control. Mariana disaster. Brumadinho disaster.

JEL codes: C58, G00, G12

the company in the stock market (see Figure 1), so it is nor clear whether the accident played a role in this shortfall or not.

Figure 1 – Daily prices of Vale ADR in NYSE, 2013-2019.

Historical market values of Vale ADR in NYSE.
Source – Google finance.

A second disaster, this time in a dam located in Brumadinho, caused at least 200 deaths, among Vale employees and citizens that could not escape quickly enough from the debris. The company's stock prices fell 24% in the aftermath of the event, causing losses of over 70 billion dollars (LAIER, 2019). Although much have been discussed in the media about the impacts for the environment and the local economy, there are not, as far as the author know, studies assessing the effect of both disasters on Vale's stock returns. Therefore, in this paper, we aim to use a causal effect methodology in order to investigate if there was an reflection of Mariana and Brumadinho's events on Vale's returns. For such, we will employ the synthetic control method, developed by Abadie & Gardeazabal (2003) and Abadie, Diamond & Hainmueller (2010).

This paper is divided in 4 sections, including this introduction. Section 2 presents the methodology of synthetic control, introducing the basic concepts and terminology, followed by the results section, on which data is presented and the results discussed. Some final remarks are made by the end of the paper.

2 Methodology

In this section we will motivate and present the methodology of synthetic control[1], following Abadie & Gardeazabal (2003) and Abadie, Diamond & Hainmueller (2010). Research in economics, as in many social sciences, lacks possibilities of doing controlled experiments due to its own nature. For example, it is not possible, in our case, to go back in time and observe Vale's returns if the Mariana disaster had not occurred in the first place. Even if we find suggestive evidence that there was a shortfall or rise in the stock prices by just observing them, it could be the case that the change was going to occur anyway, independent of having or not the disaster. Using the terminology from controlled experiments, we say that what we observe is the *factual*, e.g. the outcome observed in treatment group, and, as we shall see, it is necessary to find approximations for what is called the *counterfactual*, the outcome in a placebo group.

[1] Observação da Aisha: Em um artigo "de verdade" essa parte será bem mais resumida, mas como é para a disciplina eu quis deixar um pouco mais introdutório e apresentar os conceitos todos.

More formally, assume that $Y_i(1)$ is the observed outcome of a variable of interest when the individual i is treated (or receives treatment[2]) and $Y_i(0)$ to denote when it did not received the treatment. We are going to use $T_i = 1$ and $T_i = 0$ to indicate whether the individual received or not the treatment, respectively. It is important to notice that *never* is going to occur simultaneously $T_i = 1$ and $T_i = 0$ for the same i. Then, Y_i may be written as:

$$Y_i = Y_i(1) \times T_i + Y_i(0) \times (1 - T_i). \tag{1}$$

Notice that (1) will be $Y_i = Y_i(1)$ when the unit receives treatment ($T_i = 1$) and $Y_i = Y_i(0)$ otherwise. Therefore, we also never observe simultaneously $Y_i(1)$ and $Y_i(0)$. More important, it is not possible to observe[3] $Y_i(1)|T = 0$ and $Y_i(0)|T = 1$ because they are counterfactual. The first one is the result of the treatment in an individual that is not part of the treated group and the second is the result of not treating an individual that is in the treatment group. For example, there is no way to know what would be the result in Vale's returns if the Mariana disaster[4] had not occurred, even if we analyze years later, since there is no way to disentangle the residual effects that took place after the disaster.

To correct assess the impact of the treatment, we need to compute the average difference between the factual and counterfactual for the **treated** group:

$$\mathbb{E}[Y_i(1)|T_i = 1] - \mathbb{E}[Y_i(0)|T_i = 1] = \mathbb{E}[Y_i(1) - Y_i(0)|T_i = 1]. \tag{2}$$

Grouping the averages was only possible because we are conditioning at the same event, $T_i = 1$, but as we already argued, $\mathbb{E}[Y_i(0)|T_i = 1]$ is not observed. One naive idea would be to replace it by $E[Y_i(0)|T = 0]$, which is something we observe, in the left side of equation (2), obtaining:

$$E[Y_i(1)|T = 1] - E[Y_i(0)|T = 0]. \tag{3}$$

If we add and subtract $E[Y_i(0)|T = 1]$ (the counterfactual of the treated group) from (2), we have:

$$\begin{aligned} &E[Y_i(1)|T_i = 1] + E[Y_i(0)|T_i = 1] - E[Y_i(0)|T_i = 1] - E[Y_i(0)|T_i = 0] \\ &\quad = E[Y_i(1) - Y_i(0)|T_i = 1] + E[Y_i(0)|T_i = 1] - E[Y_i(0)|T_i = 0]. \end{aligned}$$

The terms $E[Y_i(0)|T = 1] - E[Y_i(0)|T = 0]$ are referred as *selection biases*, and it is due to the fact that both counterfactuals (the one from the treated and control groups) are not equal. In controlled experiments, control units are selected to match the treated individuals in a way that the only difference between them is the application of the treatment. In other words, in random experiments, there are no variables that differentiate the two groups, meaning that the expected value of the treated group when not receiving the treatment would be the same as the expected value of the untreated group when also not receiving the treatment.

[2] *Treatment* is being loosely used in here, only to denote that the sample unit i was affected by the event or the treatment of interest. It could be "company i suffered the disaster", for example. Then, $Y_i(1)$ would be "the returns of company i after observing the disaster in its plant".

[3] $|$ indicates the conditional. For example, $Y_i(1)|T = 0$ may be read as "$Y_i(1)$ given that $T = 0$ occurred".

[4] We are referring to Mariana disaster as example but it could be Brumadinho as well.

Stating the problem as a regression model, we could have been interest in measuring the value of Y_i including a dummy regressor T_i to indicate the treatment:

$$Y_i = \alpha + \beta T_i + X_i'\delta + \varepsilon_i. \tag{4}$$

Under the assumption that the error term is independent of both treatment status and the other covariates (which means that the units were assigned to the treatment disregarding their characteristics), we would have $\mathbb{E}[\varepsilon_i|T, \bar{X}] = 0$, implying that:

$$\mathbb{E}[Y_i|T_i = 0, \bar{X}] = \alpha + \bar{X}\delta \tag{5}$$
$$\mathbb{E}[Y_i|T_i = 1, \bar{X}] = \alpha + \beta + \bar{X}\delta. \tag{6}$$

And it is possible to show that the difference between the two equations gives us β:

$$\mathbb{E}[Y_i|T_i = 0, \bar{X}] - \mathbb{E}[Y_i|T_i = 1, \bar{X}] = \alpha + \bar{X}\delta - (\alpha + \beta + \bar{X}\delta) = \beta,$$

meaning that $\beta = \mathbb{E}[Y_i|T_i = 0, \bar{X}] - \mathbb{E}[Y_i|T_i = 1, \bar{X}]$. Unfortunately, in non-random experiments, it is hardly the case where $\mathbb{E}[\varepsilon_i|T_i, \bar{X}] = 0$. This implies that our estimate will present a selection bias:

$$\beta = \mathbb{E}[Y_i|T_i = 0, \bar{X}] - \mathbb{E}[Y_i|T_i = 1, \bar{X}] + \underbrace{\{E[\varepsilon_i|T_i = 1, \bar{X}] - E[\varepsilon_i|T_i = 0, \bar{X}]\}}_{\text{Selection bias}}. \tag{7}$$

We will refer to $\{\mathbb{E}[Y_i(1) - Y_i(0)|T_i = 1]\}$ as the *Average treatment effect over treated* (ATT); $\{\mathbb{E}[Y_i(1)|T_i = 1] - E[Y_i(0)|T_i = 0]\}$ is the *Average treatment effect* (ATE) and $\{\mathbb{E}[Y_i(1) - Y_i(0)|T_i = 0]\}$ as the *Average treatment effect over non-treated*. Notice that in random experiments $ATE = ATT$ due to the assumption of $\mathbb{E}[\varepsilon_i|T_i, \bar{X}] = 0$. This motivates the search for suitable alternatives in order to replace this assumption and still get (at least approximately) unbiased results.

This problem gave rise to the so-called *causal models*, in which different approaches, suitable depending on the existing assumptions, are employed in order to obtain good estimates for the ATT. We are not presenting all these models here, but we refer the interested reader to Ravallion (2001) for a comprehensive and introductory review. In the following subsection we will present in more detail the methodology of synthetic control.

2.1 Synthetic control

The idea behind the synthetic control method (SMC) is to create an artificial control unit, in which the characteristics prior the treatment or intervention were approximately the ones observed in the treated unit. This assumption is called *symmetry assumption* (HAHN; SHI, 2017). Intuitively, if both trajectories in the pretreatment period are roughly the same, then the differences found in the outcome after the treatment would be an indicative of causal effect (MCCLELLAND; GAULT, 2017). Therefore, our challenge is to find a way to correctly build this synthetic group in order to match the equal trajectories assumption[5].

The synthetic unit is build by weighting potential controllers from a "control pool", which has only units not affected by the treatment. Formally, we are solving the following constrained optimization problem:

$$\begin{aligned} \underset{p \in P}{\text{minimize}} \quad & (X_0 - X_1 P)' W (X_0 - X_1 P) \\ \text{where} \quad & P = \{(p_2, \ldots, p_C)'\} \\ \text{subject to} \quad & \sum_{i=2}^{C} p_i = 1, p_i \geq 0,\ i = 2, \ldots, C. \end{aligned} \tag{8}$$

In (8), X_0 is a column vector with all covariates used to explain our interest variable[6], but evaluated for the treated unit; X_1 is the analogous for the control pool. This way, the term $(X_0 - X_1 P)$ represents the distance between the covariates between the treated and untreated units. If the weights W are adequately calibrated, then the differences between the groups found in post intervention can be attributed to the treatment.

The method relies basicaly in graphical analyses, ploting the trajectories of both synthetic and treatment. Some extensions are already available, such as the generalization from Xu (2017) that allows heterogeneity in the controls and multiple treated units/treatment points. Nevertheless, since this is a preliminary work, we will follow the most basic model as proposed by Abadie, Diamond & Hainmueller (2010) and implemented in R by Abadie, Diamond & Hainmueller (2011).

3 Results

Results are divided in two in order to accommodate both disasters. We consider, as supported by media coverage and data from the market, that Vale has recovered the prices of its stocks after the Mariana disaster to the original levels prior the Brumadinho disaster, which allows us to split the sample and to construct two models, one for each disaster. This section is divided in three subsections: in the first we describe the data and the selection of the sample units, then we proceed to show the final composition of the synthetic units for both models. The main results section is also divided between Mariana and Brumadinho. Finally, we show some diagnosis for this particular models.

3.1 Data

Since there are not many mining companies listed in Brazil's stock market and the assumption of non-interference between sample units would be possible violated due to the market power of Vale in Brazil, we opted to expand the search to get stock information from mining companies listed in NYSE (Table 1).

We removed from the analysis companies with many missing data points (considering the period from 2014-01-01 to 2019-03-01) and companies presenting outliers. Data

[5] Other assumptions that should be met are: 1) only the treated unit are effectively affected by the treatment (which can be easily violated in situations where we are analyzing neighbour cities and the effect of rain, for example); 2) the treatment cannot have effect prior to its administration (which could happen in cases when analyzing legislation).

[6] It is not unusual to include $Y(1)$ itself in these vector

Table 1 – Mining companies listed in NYSE

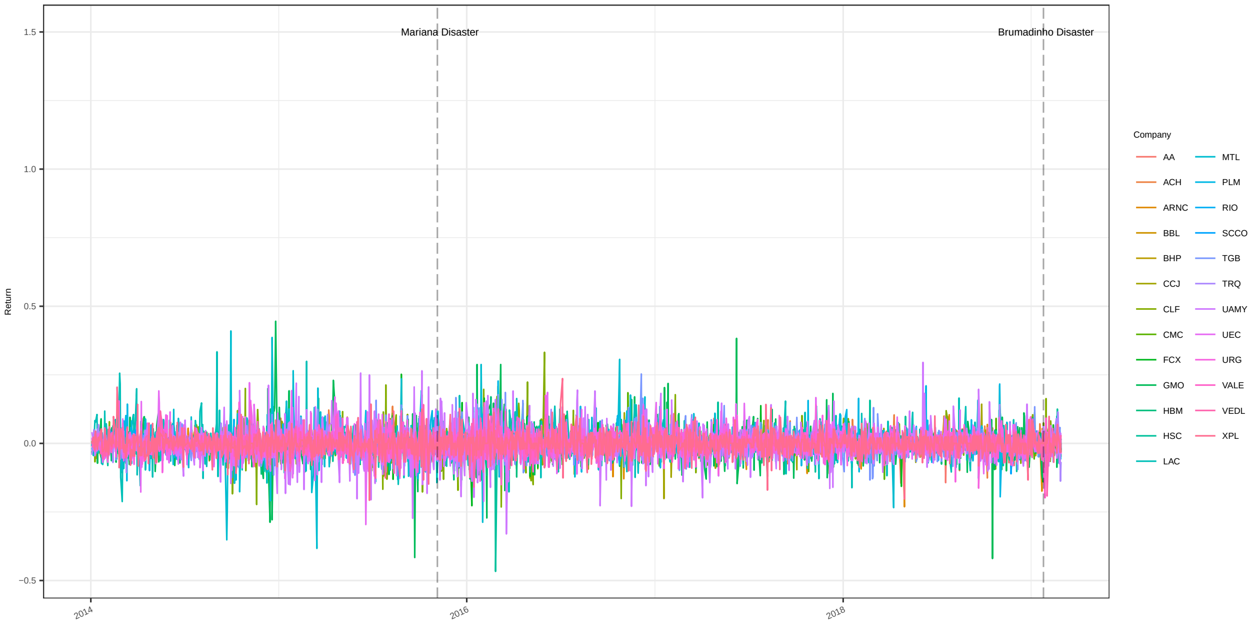
Name	**Symbol**	**Name**	**Symbol**
BHP Billiton Ltd ADR	BHP	HudBay Minerals	HBM
BHP Billiton ADR	BBL	Harsco	HSC
Rio Tinto ADR	RIO	Nexa Resources	NEXA
Vale ADR	VALE	Mechel Pref ADR	MTL-P
Arconic Pref	ARNC-P	Mechel ADR	MTL
Southern Copper	SCCO	NexGen Energy	NXE
Freeport-McMoran	FCX	Lithium Americas	LAC
Aluminum China ADR	ACH	Uranium Energy	UEC
Arconic Inc	ARNC	Polymet Mining	PLM
Vedanta Ltd	VEDL	Taseko Mines	TGB
Alcoa	AA	Ur Energy	URG
Cameco	CCJ	Platinum Group Metals	PLG
Turquoise Hill Resources	TRQ	United States Antimony	UAMY
Cleveland-Cliffs	CLF	General Moly	GMO
Commercial Metals	CMC	Solitario Exploration&Royalty	XPL

Mining companies listed in NYSE in May, 2019. Not all companies were used in this work due to lack of historical data or some incompabilities in the formats.
Source – Investopedia.

were obtained from Yahoo Finance using the R package BatchGetSymbols and we used the Synth package to run the models. Finally, placebo analysis used the functions available in the SCtools package. The variables used in the model were in daily frequency and comprise the daily returns (referred as Return in the tables and graphs), volume traded in a day (referred as Volume), the maximum amplitude in prices considering the same day (referred as Max. Amp.) and the difference between opening and closing prices (referred as Day Amp.).

The daily returns for the 25 companies used in the final models are in Figure 2. As expected, the noise does not allow for us to draw patterns or conclusions from the data as it is.

Figure 2 – Daily returns of the mining companies used in the analysis, 2014-2019.



Daily log returns computed daily using $log(P_t) - log(P_{t-1})$, where P_t is the stock price at day t. The dashed vertical lines indicate the Mariana disaster, occured in November, 2015 and the Brumadinho disaster, occured in January, 2019.
Source – Own construction using data from Yahoo Finance.

We subset the data in two, one for each disaster. For the Mariana event, the data goes from 2015-10-05 to 2015-12-07, and for Brumadinho disaster data ranges from 2018-12-26 to 2019-12-26.

3.2 Building the synthetic Vale

We used the algorithm based on the minimization described in (8) ir order to find the weights for each one of the controls at the different models. As we can see in Table 2, for the Mariana disaster the control group is formed by only two companies: Cleveland-Cliffs (with 21.6% of the weight) and Freeport-McMoran (with 78.4% of the weights). Table 3 has the averages of the covariates for each group (Vale, Synthetic and whole sample). In this case, the variables in groups show discrepancies that might explain the poor results obtained later.

Table 2 – Weights of the control group elements for the Mariana disaster

Name	Symbol	Weight	Name	Symbol	Weight
Alcoa	AA	0.000	Lithium Americas	LAC	0.000
Aluminum China ADR	ACH	0.000	Mechel ADR	MTL	0.000
Arconic Inc	ARNC	0.000	Nexa Resources	NEXA	0.000
BHP Billiton ADR	BBL	0.000	Polymet Mining	PLM	0.000
BHP Billiton Ltd ADR	BHP	0.000	Rio Tinto ADR	RIO	0.000
Cameco	CCJ	0.000	Southern Copper	SCCO	0.000
Cleveland-Cliffs	CLF	0.216	Taseko Mines	TGB	0.000
Commercial Metals	CMC	0.000	Turquoise Hill Resources	TRQ	0.000
Freeport-McMoran	FCX	0.784	United States Antimony	UAMY	0.000
General Moly	GMO	0.000	Uranium Energy	UEC	0.000
HudBay Minerals	HBM	0.000	Ur Energy	URG	0.000
Harsco	HSC	0.000	Vedanta Ltd	VEDL	0.000
			Solitario Exploration&Royalty	XPL	0.000

The weights are computed solving the minimization problem (8) for the covariates in the model for the period before the event (from 2015-10-05 to 2015-11-05).

Source – Own construction.

Table 3 – Averages for each covariate for Vale, Synthetic Vale and whole sample in the pre-treatment period for the Mariana dataset

Variable	Vale	Synthetic	Sample mean
Volume	28,403,387.50	3,010,457.98	3,802,233.85
Max. Amp.	0.2200	0.3780	0.3510
Day Amp.	-0.0200	0.0320	0.0130

The weights are computed solving the minimization problem (8) for the covariates in the model for the period before the event (from 2015-10-05 to 2015-11-05).

Source – Own construction.

As for the Brumadinho disaster (Table 4), we have three companies in the placebo unit (LAC, CMC and FCX), but Freeport-McMoran has a weight of only 6.2%, with the remaining 94% of the weights distributed between Commercial Metals and Lithium Americas. This may be an indication that more covariates should be included in the model. Table 5 has the averages of the covariates for each group (Vale, Synthetic and whole sample) and in comparison to Table 3, the former has more homogeneous groups, which may explain why the results were only meaningful for the Brumadinho disaster. Nevertheless, neither one of the synthetics were able to match the volume traded in Vale's stocks. This happens due to the nature of (8): since it is a multivariate optimization problem, the approach of the algorithm is to match the highest number of variables.

Table 4 – Weights of the control group elements for the Brumadinho disaster

Name	Symbol	Weight	Name	Symbol	Weight
Alcoa	AA	0.000	Lithium Americas	LAC	0.428
Aluminum China ADR	ACH	0.000	Mechel ADR	MTL	0.000
Arconic Inc	ARNC	0.000	Nexa Resources	NEXA	0.000
BHP Billiton ADR	BBL	0.000	Polymet Mining	PLM	0.000
BHP Billiton Ltd ADR	BHP	0.000	Rio Tinto ADR	RIO	0.000
Cameco	CCJ	0.000	Southern Copper	SCCO	0.000
Cleveland-Cliffs	CLF	0.000	Taseko Mines	TGB	0.000
Commercial Metals	CMC	0.510	Turquoise Hill Resources	TRQ	0.000
Freeport-McMoran	FCX	0.062	United States Antimony	UAMY	0.000
General Moly	GMO	0.000	Uranium Energy	UEC	0.000
HudBay Minerals	HBM	0.000	Ur Energy	URG	0.000
Harsco	HSC	0.000	Vedanta Ltd	VEDL	0.000
			Solitario Exploration&Royalty	XPL	0.00

The weights are computed solving the minimization problem (8) for the covariates in the model for the period before the event (from 2018-12-26 to 2019-01-25).
Source – Own construction.

Table 5 – Averages for each covariate for Vale, Synthetic Vale and whole sample in the pre-treatment period for the Brumadinho dataset

Variable	Vale	Synthetic	Sample mean
Volume	28,544,147.62	2,470,501.89	2,652,642.66
Max. Amp.	0.4590	0.4290	0.3970
Day Amp.	0.0100	0.0350	0.0880

The weights are computed solving the minimization problem (8) for the covariates in the model for the period before the event (from 2015-10-05 to 2015-11-05).
Source – Own construction.

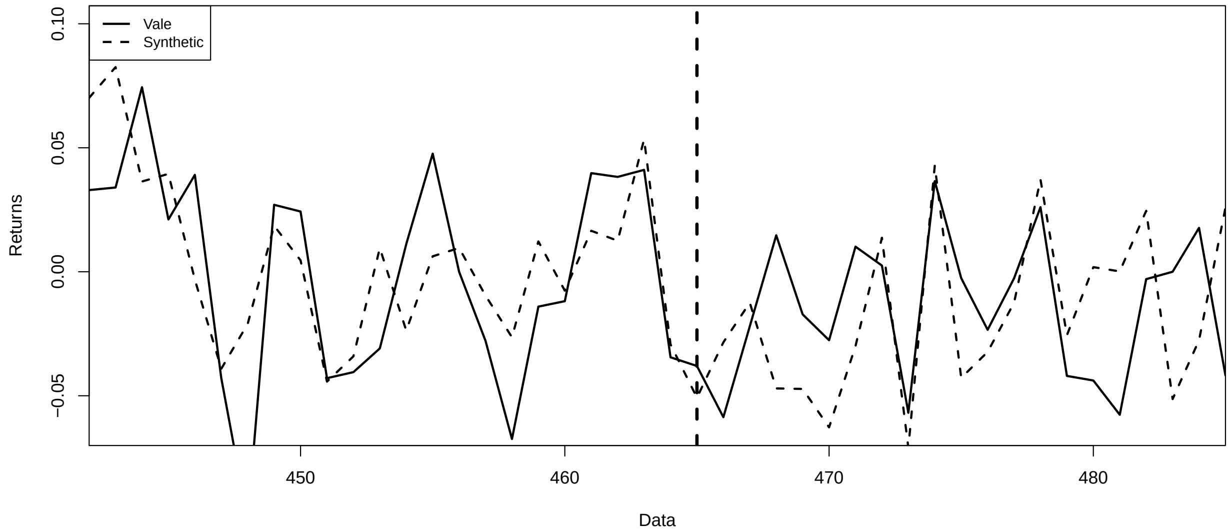
3.3 Main results

As stated previously, the SCM is based primarily in graphic analysis, which corresponds to plotting the trajectories of the outcome variable observed for the treated unit (in our case, the actual returns of Vale) against the returns of the Synthetic. We did this procedure for both datasets and they are discussed below.

3.3.1 Mariana Disaster

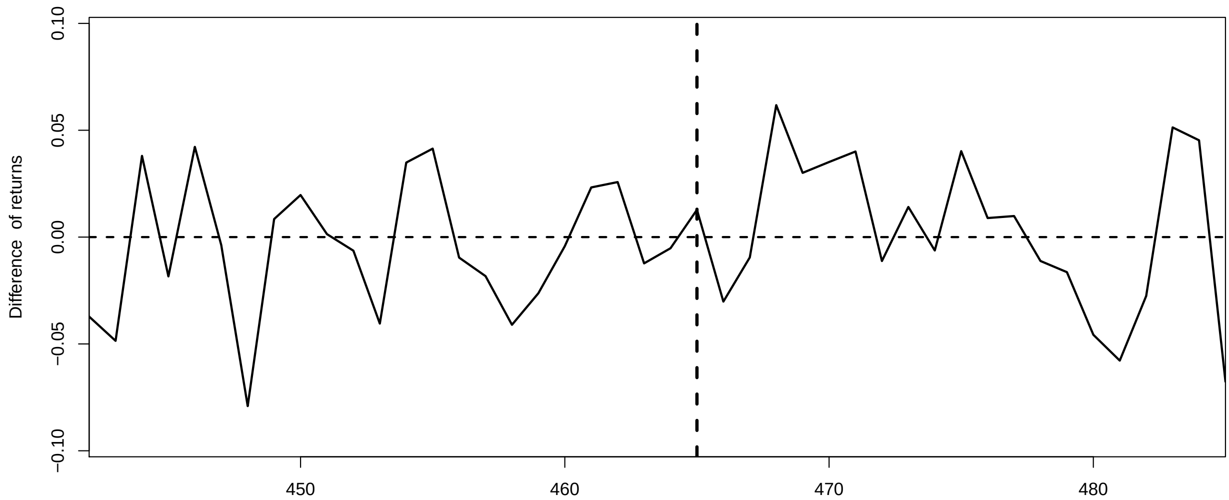
For the Mariana disaster, we cannot identify a change in the trajectories from the actual Vale returns and the returns of the placebo (Figure 3). This is evidenced when we plot the difference between these two trajectories (Figure 4), where no visible pattern emerges.

Figure 3 – Trajectories for the Vale returns and the Synthetic returns before and after the Mariana disaster.



Daily log returns observed for Vale and daily log returns computed for the synthetic unit. The dashed vertical line indicate the Mariana disaster, occured in November 05, 2015.
Source – Own construction.

Figure 4 – Differences between the Vale returns and the Synthetic returns before and after the Mariana disaster.



Differences between the plotted lines from Figure 3. The dashed vertical line indicate the Mariana disaster, occured in November 05, 2015. Negative values indicate that the return of Vale was inferior to the return of its synthetic, and positive values indicate that Value had higher return than the synthetic.
Source – Own construction.

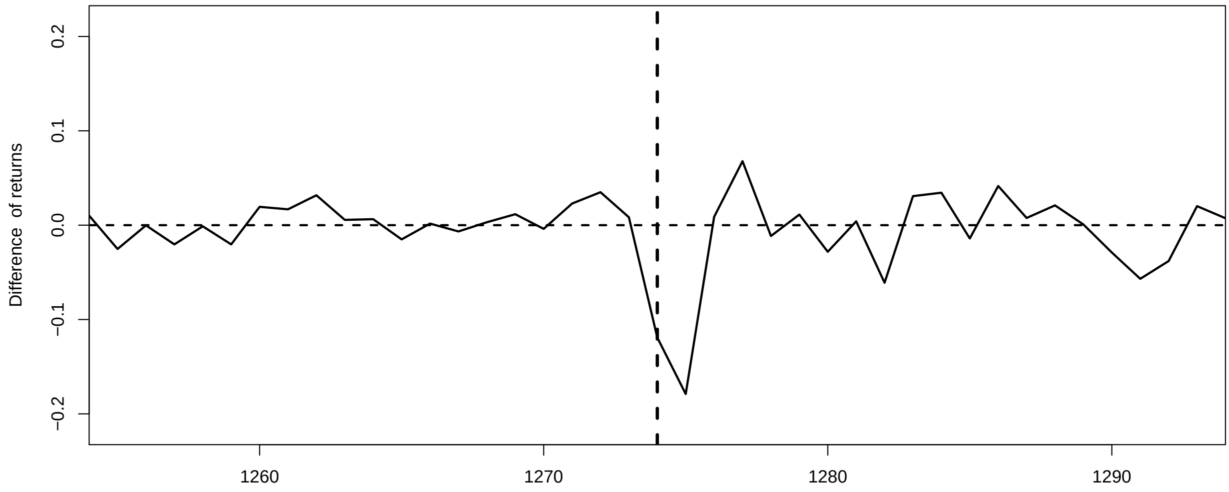
3.3.2 Brumadinho Disaster

For the Brumadinho disaster, it is possible to observe a clear shortfall in Vale returns on the proximity of the disaster (Figure 5). In the differences plot (Figure 6) the pattern is clear: on the proximity of the disaster there is a shortfall of Vales stocks (henceforth the negative value) and in the remaining periods there is no significant differences between Vale's returns and the synthetic returns.

Figure 5 – Trajectories for the Vale returns and the Synthetic returns before and after the Brumadinho disaster.

Daily log returns observed for Vale and daily log returns computed for the synthetic unit. The dashed vertical line indicate the Brumadinho disaster, occurred in January 25, 2019. Since the time variable is continuous and the disaster occurred on a Sunday, there is the false impression that the fall began before the event, but in reality this is the extrapolation from Friday closing values to the next Monday morning opening of NYSE.
Source – Own construction.

Figure 6 – Differences between the Vale returns and the Synthetic returns before and after the Brumadinho disaster.

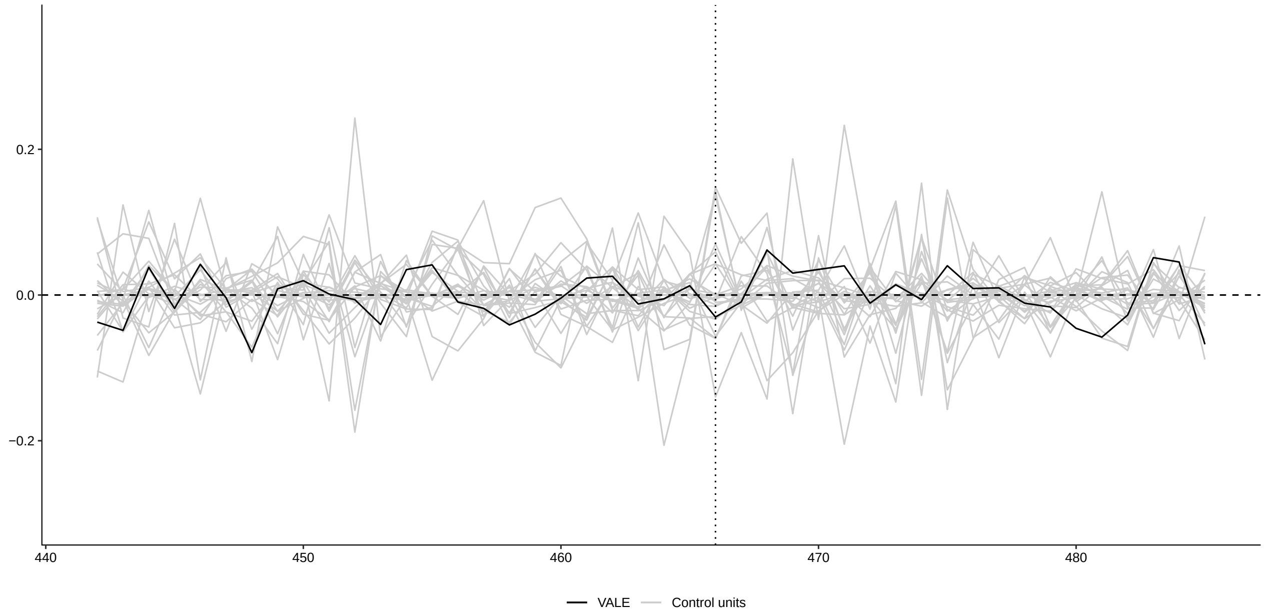


Differences between the plotted lines from Figure 5. The dashed vertical line indicate the Brumadinho disaster, occurred in January 25, 2019. Negative values indicate that the return of Vale was inferior to the return of its synthetic, and positive values indicate that Value had higher return than the synthetic.
Source – Own construction.

3.3.3 Placebo control

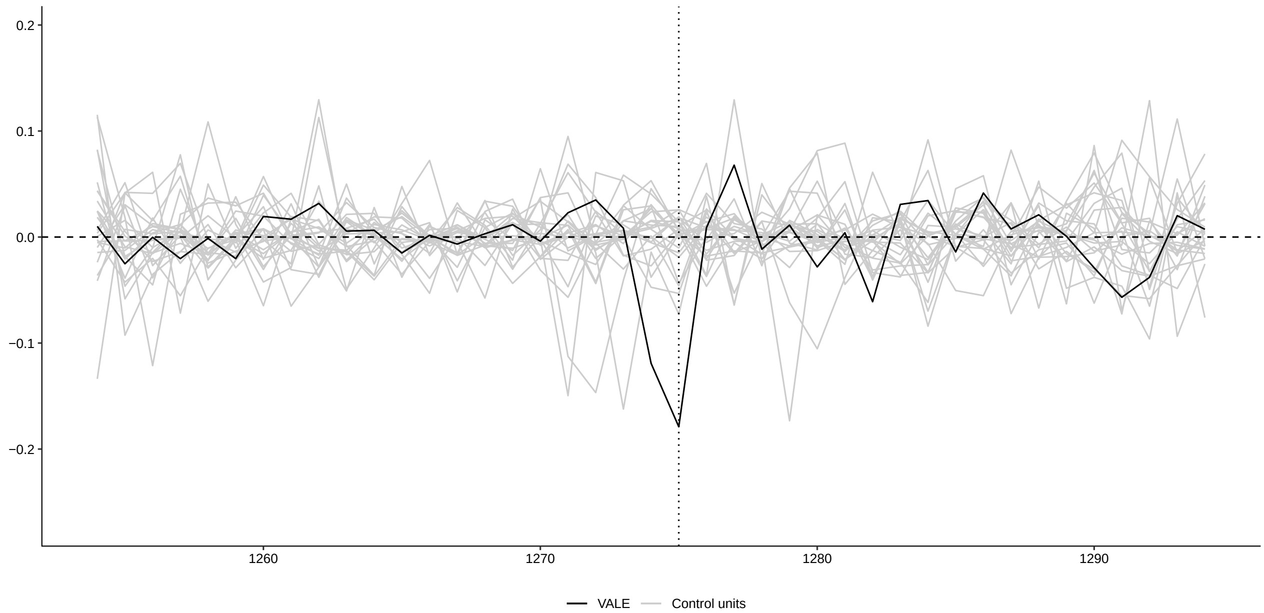
Since SCM is not a method that produces confidence intervals or p-values, is is customary to use the so-called placebo analysis as verification of good fitness of the results. The method consists in swapping the treatment unit in the model by each one of the control's pool units. For our analysis, this is exhibit in Figures 7 (Mariana data) and 8 (Brumadinho data). It is possible to see that the Vale's actual returns, represented by the black line, are in the middle of the placebos, which indicates that indeed the lack of results found in the previous subsection remains the same when changing the specification of the model. On the other hand, when we observe Figure 8 we see a clear shortfall of Vale's returns that is not followed by any of the placebo units. Nevertheless, right in the following days after the accident, the returns went back to their average values around zero.

Figure 7 – Placebo and Vale trajectories considering the Mariana dataset.



Simulation of different trajectories considering each one of the donor's pool units as the treated component (gray lines) and the actual estimated model (black line). The dashed vertical line indicate the Mariana disaster, occured in November 05, 2015. Since the black line does not differ from the placebo lines, we can infer that after the event there was no significant changes in Vale's returns.
Source – Own construction.

Figure 8 – Placebo and Vale trajectories considering the Brumadinho dataset.



Simulation of different trajectories considering each one of the donor's pool units as the treated component (gray lines) and the actual estimated model (black line). The dashed vertical line indicate the Brumadinho disaster, occurred in January 25, 2019. Since the black line has a different pattern from all the placebos in the dates immediately following the event, we can infer that the results were not due by chance.
Source – Own construction.

4 Final remarks

In this paper, we made a preliminary investigation on the effect on Vale's returns of the Mariana and Brumadinho disasters that occurred in 2015 and 2019, respectively. For such, we used the synthetic control method, proposed by Abadie & Gardeazabal (2003) and Abadie, Diamond & Hainmueller (2011). Our results show that Vale's returns apparently suffered little to no effect immediately following the Mariana disaster, but they suffered a downfall after the disaster of Brumadinho, which is supported by the analysis of placebo controls. Nevertheless, the returns went back to their original levels, which suggests that the market accommodated the shock caused by the disaster.

Future developments include changing the response variable, since returns are expected to be zero, on average. One good candidate would be the price, but some padronization to remove effect of industry size might be needed. We also intend to add in the model other covariates, including data from the companies balance sheets. This would require changes in the frequency of the data or a more sophisticated model that would allow for data to be in different frequencies.

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