Sovereign risk announcements effect on Ibovespa: an Artificial Counterfactual approach

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Abstract

Sovereign risk assessments play a crucial role in financial markets, especially in developing countries. Changes in Credit Rating Agencies' appraisals can trigger a substantial restructuring of international portfolios. In this sense, we investigate the impact of credit risk announcements regarding Brazilian bonds on the local stock market. Relying on the Artificial Counterfactual approach, we check the presence of abnormal returns within the 15 days before and after these events. Our findings indicate that credit news alters the Ibovespa return in the short run. The effects of outlook and credit watch improvement events are more potent than their rating equivalents. On the other hand, downgrade episodes might alter market conditions in the opposite direction, depending on whether a rating or outlook/credit watch change announcement was made. Although there are no signs of abnormal returns two weeks before outlook and credit watch events, the results related to rating change announcements are mixed.

Keywords: Sovereign rating; Stock market; Event study; ArCo.

JEL Codes: E44, G14, G15, G32

Area - Macrofinance

1 Introduction

Credit Rating Agencies (CRAs) play a relevant role in international financial markets by providing a forward-looking evaluation of the probability of sovereign debt default. These assessments are represented primarily through sovereign credit ratings, which indicate a government's ability and willingness to pay its domestic (foreign) debt within the given time frame (Cantor and Packer, 1996). In this regard, it summarizes a country's likelihood of default, providing crucial information for economic agents (Afonso et al., 2011).

Although not explicitly disclosed, it is known that the main CRAs use a combination of quantitative and qualitative variables to determine a country's sovereign rating.[1] According to Standard & Poor's (2022), quantitative variables cover different economic and financial performance measures, such as economic growth, financial stability, inflation, fiscal performance, external liquidity, and public debt service. On the other hand, qualitative aspects include political risks, level of democracy, government transparency, and corruption. It is important to highlight that CRAs issue sovereign ratings at the request of governments and in exchange for a fee, which might open a debate regarding the degree of subjectivity in sovereign ratings (De Moor et al., 2018).

CRAs' assessments are important in financial markets since sovereign ratings are fundamental in attracting international capital, especially in developing countries. This is notably true for several pension funds from developed countries, which are required by law to invest exclusively in assets with the "Investment Grade" label. Therefore, changes in CRAs' assessments are crucial events that can trigger substantial changes in the restructuring of international portfolios (Brooks et al., 2004). In turn, these capital movements might affect the stock market, particularly during the days following such events. Indeed, there is enriched literature regarding the impact of sovereign credit news on different features of the stock market, such as its return (e.g., Bissoondoyal-Bheenick, 2004; Mutize and Gossel, 2018), volatility (e.g., Hooper et al., 2008; Tran et al., 2014) and liquidity (e.g., Lee et al., 2016).

Sovereign ratings are the primary instrument used by the CRAs to indicate permanent changes in countries' credit quality. Likewise, CRAs can modify market conditions by disclosing potential rating changes through outlook and credit watch status. This sort of credit news provides the possible direction and timing of future changes in the sovereign rating (Hamilton and Cantor, 2004). Regarding their economic function, Bannier and Hirsch (2010) point out that CRAs disclose signals of potential changes in the sovereign rating in order to reduce information asymmetry in

[1] The main CRAs are Fitch Ratings, Moody's and Standard & Poor's, also known as the "Big Three". These three agencies concentrate approximately 95% of the rating business.

the market. In addition, several studies suggest that outlook and credit watch status are as important as sovereign ratings in affecting international financial markets (e.g., Norden and Weber, 2004; Baum et al., 2016). The findings of Kaminsky and Schmukler (2002) indicate that credit signals issued through outlook and credit watch are more effective in changing the conditions of capital markets in emerging countries.

With this in mind, this paper aims to investigate the impact of sovereign credit risk change announcements on the Brazilian stock market (Ibovespa) return from 2002 to 2022, both in terms of rating and outlook/credit watch status changes. Some works investigated the effect of sovereign rating changes on the Ibovespa index (e.g., Markoski and Moreira, 2010; Almeida, 2010; Barros and Colauto, 2020). They all applied an event study analysis relying on MacKinlay (1997). In this framework, an abnormal return is estimated based on the difference between the observed return and a "normal" return, considered as the one that would take place if the event had not occurred. When examining the impact on the stock market altogether, the "normal" return of Ibovespa is estimated according to the adjusted mean return model, which assumes that the mean return of a given security is constant over time.

Following the finance literature, we also rely on a traditional event study approach. However, we distinguish our work by considering a CRA credit risk change announcement as a supposed intervention experienced by the stock market. In other words, our study deals with the issue in a Treatment Effect context, applying one of the most prominent techniques – Artificial Counterfactual (ArCo) – developed by Carvalho et al. (2018). This approach is handy when a control group is unavailable and one element is subjected to the treatment, which can be viewed as the case when a CRA announces a change in its assessment related to the default likelihood of Brazilian bonds.

The ArCo method estimates the average treatment (intervention) effect on the treated unit in a two-step procedure. In the first step, a multivariate model is estimated based on a high-dimensional panel of time-series data from a set of untreated peers. In order to provide robustness to our results, we employ three Machine Learning (ML) algorithms: Least Absolute Shrinkage and Selector Operator (LASSO), Random Forest, and Neural Networks. These three ML algorithms have been applied to forecast stock market returns with promising results (e.g., Coqueret and Guida, 2018; Freyberger et al., 2020; Chen et al., 2023). Furthermore, our untreated peers panel abides by more than forty stock market indexes from developed and undeveloped countries. Still, we were careful enough not to include countries that could have their stock market affected by changes in the perception of Brazil's sovereign risk, such as the South American countries.

In the second step, a counterfactual series is built by extrapolating the model with data after the intervention. In our paper, this artificial series might be perceived as the "normal" return, i.e., what would happen to the stock market return if the

CRA had not announced any change in its perception of credit risk. Therefore, we avoid assuming a constant return would occur if the event had not materialized. The mean difference between the observed and the normal return provides us with the Average Abnormal Return (AAR). Based on the AAR, we can compute the Cumulative Abnormal Return (CAR) over the days following the announcement.

Considering 36 announcement events, we calculate the AAR and the CAR for the following 15 working days to investigate whether these announcements can impact stock market return in the short run. Our analysis initially seeks to answer three questions. Do rating and outlook/credit watch status change announcements affect the stock market return? If so, do they have the same effects? Is there any asymmetric impact regarding upgrade and downgrade events? Although other works have tried to answer these same questions, none have applied last-generation ML algorithms to build a robust counterfactual.

Our findings indicate that both rating and outlook change announcements alter the short-run return path of the Ibovespa Index. In particular, outlook improvement announcements' effects are more potent than their rating equivalents, with a CAR of around 3,49% and 2,82%, respectively. This result is expected and agrees with the literature's general findings. Investors often anticipate a rating change based on an issue's outlook status, which is precisely the role of the last, i.e., reducing the asymmetry of information regarding future changes in CRAs' assessment.

On the other hand, downgrade episodes might alter market conditions in the opposite direction, depending on whether a rating or outlook change announcement was made. An outlook downturn event reduces the stock market return with a CAR of roughly 2,03%, whilst a rating downgrade increases the market return with a CAR of 5,31%. This result links us to the third question. Indeed, there is a sort of asymmetry among upgrade and downgrade events since downgrade announcement effects seem stronger than upgrade ones. However, our findings suggest an upward market return in the event of a rating downgrade and not the opposite, as many studies indicate (e.g., Brooks et al., 2004; Markoski and Moreira, 2010; Mutize and Gossel; 2018; Riaz et al., 2018). Notwithstanding, an inverse relationship between sovereign risk perception and stock market return in the days following a downgrade announcement had already been found in the literature that studied the Brazilian case (e.g., Almeida, 2010). We interpret this counterintuitive result as investors reacting to market opportunities.

As several studies point out, there is the potential for noisy information in the days before the event, which might deviate market return from some "normal" behavior even before CRA's official announcement (Castro-Iragorri, 2019). In turn, the estimated abnormal returns might hide the actual market response. We investigate this issue by shifting the event day to 15 working days before the official announcement and estimating the AAR and the CAR over these days. Our findings indicate that the market does not anticipate announcements of outlook and credit watch status changes. Mixed results are found in terms of a rating change event.

Our work contributes to the literature in a few ways. To the authors' knowledge, we are the first to employ artificial counterfactual estimation to calculate the stock market's abnormal return due to CRA announcements. Castro-Iragorri (2019) developed a closed-related study employing a Synthetic Control Method (SCM) to estimate the abnormal return in mergers and acquisitions. His findings suggest that causal inference methods such as SCM or difference-in-differences do not improve the traditional approach based on the fitted market model. In addition to being a different subject, our work applies a distinct method, making use of Tree-based and Deep Learning ML approaches.

Furthermore, we update and expand the works of Markoski and Moreira (2010) and Almeida (2010). These papers cover a different and smaller sample period and employ the mean-adjusted return model. Our sample period covers different economic scenarios, from the commodities boom in the early 2000s to the COVID-19 pandemic, through the financial crisis of 2008/09 and the deep domestic recession of 2015/16. These periods are marked in terms of sovereign ratings, given that Brazil gained the Investment Grade label in 2008/09 and lost it in 2015/16. Other works, such as Brandão (2015), Klotzle et al. (2016), and Barros and Colauto (2020), investigate the effect of sovereign rating changes not in the stock market as a whole but in a subset of stocks — state-owned stocks, for instance. Hence, our paper put to the test previous results by applying an alternative approach and the most recent data-driven statistical algorithms. In this sense, our work might be relevant to market agents in general, particularly retail investors.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the method and data used in the empirical analysis. Section 4 discusses the main results regarding the rating and outlook events separately. Section 5 provides a further analysis by investigating potential market anticipation. Finally, section 6 concludes the paper.

2 Literature Review

The literature that examines the impact of sovereign rating change on financial and macroeconomic indicators is rich. For instance, there is ample empirical evidence indicating that an increase in sovereign ratings can help to attract international capital flows (e.g., Kim and Wu, 2008), lower credit default swap (CDS) spreads (e.g., Binici and Hutchison, 2018) and corporate lending spreads (e.g., Drago and Gallo, 2017), appreciate the domestic currency (e.g., Alsakka and Gwilym, 2012) and reduce the disagreement in expectations related to the exchange rate (e..g, de Oliveira and Montes, 2020). Besides, sovereign bonds can affect economic activity through private investment and financing decisions (e.g., Chen et al., 2013; Almeida et al., 2016).

Considering works that exclusively investigate the effect of sovereign rating changes on the stock market, Brooks et al. (2004) examine several developed and undeveloped countries from 1973 to 2001. They report that rating downgrades harm market returns, but only Standard Poor's and Fitch announcements have significant effects. Hu (2017) makes a similar analysis but restricts it to bank stock returns in the eurozone. Some results show that positive sovereign rating events do not lead to significant reactions in bank stock prices. In contrast, adverse events are associated with negative share price effects on domestic banks.

Based on a comprehensive database of 42 countries from 1995 to 2003, Hopper et al. (2007) findings indicate that rating upgrades (downgrades) increase USD-denominated stock market returns and reduce (rise) volatility. Besides, the market response is more noticeable in the case of downgrades. Bales and Malikane (2020) focus on emerging market volatility. Again, the findings provide evidence of an asymmetric effect since downgrades significantly impact stock volatility, while upgrades have no such effect.

The literature also explores potential spillover and competitive effects in international stock markets. For instance, Ferreira and Gama (2007) empirical evidence suggests sovereign rating and credit outlook changes in one country have an asymmetric and economically significant effect on the stock market returns of other countries. While downgrade events promote an adverse market reaction, upgrades have no significant impact on the return spreads of countries abroad. In addition, emerging market status amplifies the spillover effect. Bissoondoyal-Bheenick (2012) analyzes the spillover effect in the 17 Asia Pacific Economic Cooperation (APEC) stock markets. Its findings suggest that the contagion effect is more significant when the country experiencing a change in its sovereign rating has high financial integration with the unaffected country, especially when compared to countries with high trade integration.

A vast part of the literature that examines the impact of sovereign rating changes on the stock market relies on an event study approach. This is a natural path to follow once one can classify a rating change announcement as an event that takes place on a specific calendar day. In addition, the daily frequency of stock market data allows the inspection of the effect in a short time window, which is suitable to assume any exogenous influences other than the given event. According to MacKinlay (1997), in this framework, an abnormal return is estimated based on the difference between the observed return and a "normal" return, considered as the one that would occur if the event had not happened in the first place. Many works that investigate the impact of CRA credit announcements on the Ibovespa index or on a subset of stocks follow this approach.

For instance, Markoski and Moreira (2010) investigated whether the Ibovespa return was affected by ratings and outlook status change announcements from 1994 to 2003. The study includes almost 30 rating and outlook change events and aims to inspect potential effects during the 20-day window around the official disclosure day. The authors consider the adjusted (constant) mean return model to calculate the Ibovespa “normal” return. Their findings indicate that negative announcements have greater effects than positive ones, and negative news appears to be anticipated by market agents.

Almeida (2010) followed the same strategy and applied the adjusted mean return model in his analysis of the impact of sovereign rating changes on the Ibovespa return and country risk spread. Based on 21 events from 2001 to 2010, in a 15-day window around the announcement day, his results indicate a substantial negative impact on the Ibovespa return in many days around downgrade events but no effect on the country risk spread.

Other works investigate the credit risk change announcement in a subset of stocks rather than the whole market index. In this case, it is possible to build a “normal” return series based on a market model, which usually uses the Ibovespa index. In this case, a model linearly relates the return of a given stock to the return of the market portfolio (Ibovespa index), with each stock having its own estimated parameters.

For instance, Roth et al. (2012) focuses on the 10 stocks with higher trade volume from 2001 to 2010. His findings reveal that Petrobras’ stocks performed above the average in the face of a rating upgrade event. Contrary to most literature findings, rating upgrade announcements had a more substantial effect than downgrade ones. In a similar analysis, Klotzle et al. (2016) spotlights only state-owned company stocks from 2002 to 2014. Employing a market model analogous to Roth et al. (2012), their findings point out that downgrade announcements are associated with a significantly positive CAR. In particular, negative events increase the CAR by roughly 8.6%.

Both the adjusted mean return model and the market model have their drawbacks. The first assumes that the mean return of a given market index is constant over time, which might not be the case. The second is not applicable when one seeks to estimate the “normal” return of the whole stock market. The market model may not be suitable even when the aim is to estimate a set of stocks’ returns. This happens because this approach assumes that the event does not affect the market index, so the last can be used to construct the counterfactual return series. However, as the above-mentioned studies suggest, this assumption is hard to maintain in a sovereign rating change event. To avoid such disadvantages, we rely on the ArCo approach, which allows us to estimate a contrafactual market return based on an untreated peer group of variables. This is achieved through the application of well-recognized ML algorithms.

Due to the exponential increase in the computational capacity of modern computers and data gathering by governments and companies in recent decades, ML methods have been applied in the most diverse fields of science. In economic sciences, it has been no different. In the banking sector, for example, it is already usual to use ML methods to classify the credit risk of individuals and legal entities (e.g., Hardle et al. 2009; Cubiles-De-La-Vega et al., 2013; Moscatelli et al., 2020). In addition, such methods can be used to forecast several macroeconomic variables (e.g., Hall, 2018; Maehashi and Shintani, 2020; Richardson et al., 2021).

Moreover, many works have employed ML algorithms to forecast stock and market returns in recent years. For instance, Freybergeret al. (2020) applied the LASSO method to determine which firm characteristics provide independent information for the cross-section of expected returns. Based on US market data from 1963 to 2015, their results imply that many of the previously identified return predictors do not provide incremental information. Besides, their proposed method has higher out-of-sample explanatory power than linear panel regressions.

Similarly, Coqueret and Guida (2018) build regression trees to determine which firm characteristics are most likely to drive future stock returns in the US in the sample period of 2002-2016. Out of 30 financial and accounting variables, those related to momentum appear to have the most marked impact. On the other hand, Chen et al. (2023) choose a deep learning approach to estimate an asset pricing model for individual stock returns. Following this strategy, their method outperforms in the out-of-sample period, providing lower pricing errors.

3 Methodology and Data

3.1 Methodology

The ArCo method estimates the causal effects of an intervention on a single treated unit when a control group is not readily available. Its framework consists of a two-step procedure. In the first step, a multivariate model is estimated based on a high-dimensional panel of time-series data from a set of untreated peers ("donors pool"). In the second step, a counterfactual series is built by extrapolating the model with data after the intervention. The method can be seen as an extension of the SCM of Abadie and Gardeazabal (2003) and Abadie et al. (2010) and the Panel Factor method put forward by Hsiao et al. (2012). Lately, it has been applied to estimate the health and economic effects of the lockdown measures in the US and Brazil during the COVID-19 pandemic (e.g., Carneiro et al., 2021; Maranhão, 2021), as well as to examine the impact of political shocks on financial and macroeconomic variables in the Brazilian scenario (e.g., Mariz, 2020; Allen, 2021).

Based on Carvalho et al. (2018) and Fonseca et al. (2018), the ArCo framework can be briefly described below. Assume n units (such as stock market indexes) are indexed as $i = 1, ..., n$. For each unit and time period $t = 1, ..., T$, one can observe q stationary series (such as return and volatility) represented by $y_{it} = (y_{it}^1, ..., y_{it}^q)'$. Without loss of generality, it can be assumed that only unit $i = 1$ (Ibovespa return) among all is affected by the event or intervention (CRA sovereign risk change announcement) in period T_0. In addition, consider that a dummy D_t assumes the value of 1 (one) after the event and 0 (zero) otherwise. Hence, the observed variables of the unit 1 can be written as:

$$y_{1t} = D_t y_{1t}^{(1)} + (1 - D_t) y_{1t}^{(0)} \tag{1}$$

where $y_{1t}^{(1)}$ is the outcome of unit 1 when it is exposed to the event and $y_{1t}^{(0)}$ is the estimated contrafactual of the treated unit, i.e., the potential outcome of unit 1 when there is no event. In this sense, the intervention can be defined as:

$$y_{1t} = \begin{cases} y_{1t}^{(0)}, & t = 1, \ldots, T_0 - 1 \\ \delta_t + y_{1t}^{(0)} & t = T_0, \ldots, T \end{cases} \tag{2}$$

where $\delta_t = y_{1t}^{(1)} - y_{1t}^{(0)}$ is the intervention effect on unit 1 on period t. Hence, the ArCo method is concerned with the following hypothesis:

$$\mathcal{H}_0 : \Delta_T = \frac{1}{T - T_0 + 1} \sum_{t=T_0}^{T} \delta_t = 0 \tag{3}$$

where Δ_T is the average treatment effect over the treatment period.

We do not observe $y_t^{(0)}$ for $t \geq T_0$. This quantity is the counterfactual, i.e., the market return in the absence of the credit risk change announcement. In order to proceed to the first step estimation of the ArCo, let us assume that we can build this counterfactual in period t according to a vector with all untreated peers, X_t, plus an error term, ϵ_t. In this sense, consider the following model for $y_t^{(0)}$:

$$y_t^{(0)} = \mathcal{M}_t + \epsilon_t \tag{4}$$

where $E(e_t) = 0$ and $\mathcal{M}_t = \mathcal{M}(X_t)$. Note that $\mathcal{M}_t$ is a measurable mapping because it does not need an explicit function.

We estimate equation (4) using the first $T_0 - 1$ observations, given that for $t < T_0$ we have $y_t = y_t^{(0)}$. Then, one can estimate $\widehat{M_t} = \widehat{M}(X_t)$ using the data before the event and employ it to construct the counterfactual:

$$\widehat{y_t}^{(0)} = \begin{cases} y_t^{(0)}, & t = 1, \ldots, T_0 - 1 \\ \widehat{M_t} & t = T_0, \ldots, T \end{cases} \tag{5}$$

Finally, the ArCo estimator is defined as:

$$\widehat{\Delta}_T = \frac{1}{T - T_0 + 1} \sum_{t=T_0}^{T} \widehat{\delta}_t \tag{6}$$

where $\widehat{\delta}_t = y_t - \widehat{y}_t^{(0)}$ and $t = t_0, \cdots, T$.

The ArCo approach is flexible enough to allow us to analyze multiple events. In this way, suppose we have S-ordered known event points corresponding to the fraction of the sample given by $\lambda_0 \equiv 0 < \lambda_1 < \cdots < \lambda_s < 1 \equiv \lambda_{s+1}$. For each event point $s = \{1, \cdots, S\}$, we can determine the time of each event by $T_s \equiv [\lambda_s T]$ and build our estimator in the same manner we do for the single event case. To facilitate notation, let us define the set of all periods after event s but before event $s+1$ as $\tau_s = \{T_s, T_s + 1, ..., T_{s+1} - 1\}$ and define $\#\{A\}$ as the number of elements in the set A. Then, we have S estimators given by:

$$\widehat{\Delta}_T^s = \frac{1}{\#\{\tau_s\}} \sum_{t \in \tau_s} \widehat{\delta}_t, \quad s = 1, \cdots, S \tag{7}$$

Note that we could allow the model to depend on s, i.e., differ from one event point to another. However, as Carvalho et al. (2018) suggested, we choose a more parsimonious approach by estimating the same model for all event periods. In turn, we can aggregate all intervention effects across upgrade and downgrade events and estimate the average intervention effect over multiple treatment periods:

$$\widehat{\boldsymbol{\Delta}}^S = \frac{1}{S} \sum_{s=1}^{S} \widehat{\Delta}_T^s = \frac{1}{\sum_{s=1}^{S} \#\{\tau_s\}} \sum_{t \in \bigcup_{s \in S} \tau_s} \widehat{\delta}_t \tag{8}$$

Therefore, based on the estimator above, one can perform the following hypothesis test:

$$\mathcal{H}_0 : \boldsymbol{\Delta}^S = 0 \tag{9}$$

In the context of our research and following the finance literature, we can rewrite the ArCo estimator of event the s as:

$$\widehat{AAR}_T^s = \frac{1}{\#\{\tau_s\}} \sum_{t \in \tau_s} \widehat{AR}_t, \quad s = 1, \cdots, S \tag{10}$$

where $\widehat{AR}_t = R_{1t} - E(R_{1t}|X_t)$ represents the abnormal return, which is the difference between the observed return, R_{1t}, and the "normal" return, i.e., what would be the potential outcome of the stock market return if the event had never happened, conditioned to the peer group of untreated units, $E(R_{1t}|X_t)$. Hence, AAR is the average abnormal return over the event window τ_s. Based on the AAR, we can compute the Cumulative Abnormal Return (CAR) over the days following the announcement s.

According to equation (8), we can estimate the AAR for all rating and outlook/credit watch status upgrade and downgrade events separately to capture asymmetric effects such as those reported by the literature.

The finance literature that performs short-term event studies on daily returns defines the event window as an interval around the event, typically 10, 5, or 1 day(s) (Castro-Iragorri, 2019). However, some works that examine the Brazilian case extended this window to 15 and 20 days around the event (e.g., Almeida, 2010; Markoski and Moreira, 2010). We chose a 15-day window after the event to compare our results with those that investigated the impact on Ibovespa exclusively. In a further analysis, we consider a potential event anticipation by conducting our examination in the 15-day window before the CRA announcement.

On the other hand, the estimation window usually lasts 1 year or 250 days of market returns. Once the literature relies on mean-adjusted return or on a market model, a large estimation window is necessary to capture the long-run path of the market return, which, in turn, will be used as a counterfactual. On the contrary, our estimation window is relatively shorter, precisely 30 days before the event. As will become more apparent in the Data description section, we handle it this way because our counterfactual comes from market indicators of other countries unaffected by the intervention. This is the same reason why we do not need to be concerned about the gap window, another common feature of event studies in Finance.

Originally, Carvalho et al. (2018) applied the LASSO structure for $\mathcal{M}_t$ in equation (4). All their asymptotic results rely on this particular method. Notwithstanding, the ArCo method allows us to employ different mapping functions, such as Tree-based and Deep Learning algorithms. In this sense, we follow the literature and apply two well-known ML methods, namely the Gradient Boosted Regression Trees (GBRT) and the Multilayer Perceptron Regression (MLP).[2]

The Grid-search cross-validation process to select the hyperparameters and evaluate their prediction performance is conducted in the following way. The training set, which consists of the pre-event period observations, is divided into k disjoints subsets of equal size, and then each of them is held out to serve as the test sample.[3] At the same time, the algorithm is trained on the remaining $k-1$ training subsets. Hence, we reduce the dependence of the learners on the randomly selected initial training and test samples (Muller and Guido, 2017). Given computational restrictions, we employ the 5-fold cross-validation procedure. The accuracy criteria for selecting the

[2]We briefly describe each of the ML applied in this study in Appendix A1.

[3]Fonseca et al. (2018) suggests an estimation window between 40 to 50 observations. Although our estimation window consists of 30 observations (or 15 in the further analysis) before each event occurs, we have much more data to train the ML. This is the case since we gathered all events to train the ML. In practice, the training set abides by $36 \times 30 = 1080$ observations ($36 \times 15 = 540$ in the further analysis).

best model is the coefficient of determination.[4]

Since we are applying two additional methods beyond the LASSO, we need to adopt a bootstrap procedure to construct the ArCo estimator distribution, which will allow us to perform hypothesis testing. Once serial correlation is an inherent issue in time series analysis, we must employ a particular bootstrap method that incorporates this matter. Hence, we act in accordance with Kunsch (1989) and Lahiri (1999) by applying the overlapping blocks bootstrap, also known as "moving-block bootstrap". The block optimal size is calculated according to Politis and White (2004) formula. Furthermore, in order to provide more reliable results, we adopt the "Bootstrap-t" which has been advocated by Hall (1992).[5][6][7]

3.2 Data

This study considers the announcement of changes in the Brazilian sovereign risk of the main CRAs as the event in which the investigation is carried out. In particular, we take into account changes in the perception of credit risk regarding long-term bonds in foreign currency. CRAs' assessments are announced in terms of a rating or an outlook/credit watch status change. Sovereign ratings indicate the likelihood of default in the long run — 2 years or more — and are represented by letter designations such as A, B and C. In this sense, the AAA/Aaa rating indicates the top rating issued by all CRAs, which has the lowest probability of default. On the other hand, lower ratings regarding the alphabetic order indicate a higher probability of default. Sovereign bonds rated equal to or above BBB-/Baa3 are considered to have an "investment grade", while those rated below BBB-/Baa3 are labeled as "speculative grade". Table 1 exhibits the rating scale of the main CRAs and briefly describes the economic meaning of all rating ranges.

Differently, the outlook and credit watch status indicate that a sovereign bond is under review or on watch for a future upgrade or downgrade of its credit rating. Credit watch signals a change in the short term (up to 6 months), while outlook indicates a potential change in the medium term (between 6 months and 2 years). The +/- signs indicate positive/negative announcements, while the label "stable" indicates no change in the current sovereign rating.

We examine the effect of CRA announcements on the Ibovespa return from 2002 to 2022. The day of each announcement was extracted from the Country Economy

[4]The hyperparameters selected for each algorithm, which provides the best prediction accuracy in the test set, are reported in Table A1 in Appendix A2.

[5]For a full-fledged discussion about several bootstrap methods used in econometric analysis, see MacKinnon (2006).

[6]The bootstrap distributions were generated from 1,000 iterations.

[7]All estimations were conducted in Python software.

database.[8] The sample period was chosen due to the data availability, mainly concerning the peer group used to construct the contrafactual. Still, the timespan covers different economic scenarios, including the commodities boom in the early 2000s, the financial crisis of 2008/09, the deep recession of 2015/16, and the COVID-19 pandemic. Table 2 presents all CRA announcements taken into consideration by this study. In total, we have 36 announcements, of which 16 are rating events and 20 are outlook/credit watch events. From these 16 rating announcements, 10 were upgrade events and 6 were downgrade ones. From those 20 outlook/credit watch announcements, half indicated an improvement in the credit risk evaluation, whilst the other half indicated deterioration in CRA assessment.

Table 1 - Sovereign rating system

Rating classification		Credit Rating Agencies		
		S&P	Moody's	Fitch
Investment grade	Extremely strong capacity to meet financial commitments	AAA	Aaa	AAA
	Very strong capacity to meet financial commitments	AA+	Aa1	AA+
		AA	Aa2	AA
		AA-	Aa3	AA-
	Very strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances	A+	A1	A+
		A	A2	A
		A-	A3	A-
	Adequate capacity to meet financial commitments, but more subject to adverse economic conditions	BBB+	Baa1	BBB+
		BBB	Baa2	BBB
		BBB-	Baa3	BBB-
Speculative grade	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions	BB+	Ba1	BB+
		BB	Ba2	BB
		BB-	Ba3	BB-
	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial conditions	B+	B1	B+
		B	B2	B
		B-	B3	B-
	Currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments	CCC+	Caa1	CCC+
		CCC	Caa2	CCC
		CCC-	Caa3	CCC-
	Highly vulnerable; default has not yet ocurred, but is expected to be a virtual certainty	CC	Ca	CC
		C	C	C
	Payment default on a financial commitment or breach of an imputed promise	SD		RD
				D

Source: Prepared by the authors

Regarding the set of untreated units used to construct the contrafactual of the Ibovespa return, we selected stock market indexes of non-South American countries based on public data availability. In particular, we included indexes with at least 85% non-missing data. We avoid using indexes with excessive missing observations since

[8] https://countryeconomy.com/

the LASSO method can not handle unbalanced panel data.[9][10] In addition, we do not include South American market indexes in order to mitigate any possible contamination from the event to the peer group, which might occur given the importance of the Brazilian economy in this geographic region. On the other hand, it is unlikely that a change in Brazil's sovereign rating or outlook/credit watch status can affect stock markets outside South America.[11]

Furthermore, we include the Bloomberg commodity index and the US real interest rate in the peer group. Since Brazil is a major commodity exporter, including a commodity price index in the "donors" pool seems reasonable. Besides, the Ibovespa index often reacts to changes in the US interest rate; therefore, we judge it prudent to incorporate the last in the peer group. All variables included in the peer group and their sources are reported in Table A2 in Appendix A2.

As usual in finance studies, we use the log return of each stock market index in the estimations. We do the same for the commodity index.[12] Predicting possible non-stationarity of the US interest rate series, we use its first difference in the analysis. Since unbalanced panel data can harm the estimations, all missing data were set equal to zero.[13] Table A3 in Appendix A2 presents the descriptive statistics of the Ibovespa index and the peer group after the above-mentioned transformations.

The index with the highest average log return in the period was the KASE from Kazakhstan, with a 0.10% return. On the other hand, the Japan index TOPX showed the lowest average, with a −0.04% return. The maximum log return in a day was 48.7%, whilst the minimum was −48.64%, both the KASE index. In turn, the Kazakhstanian index had the highest log return standard deviation, 2.89%. The lowest log return standard deviation was 0.47% from the Botswana Stock Market Index, BSE. In addition, the daily average log return of the commodity index was 0.02%, with a maximum of 4.82% and a minimum of −4.60%. The US interest rate's average change was 0.001%, with a maximum and minimum daily change of 0.75% and −0.85%, respectively.

In order to meet the stationarity requirements, all return series were subjected to ADF unit root tests. The results are displayed in Table A4 in Appendix. As expected,

[9] Although deep-learning and tree-based algorithms can handle missing data, data imbalance often negatively affects these methods.

[10] Some of the missing data is due to those days that are holidays in another country but Brazil.

[11] Ballester and González-Urteaga (2021) findings, for instance, show no signs of cross-border effects of a sovereign rating change in American underdeveloped countries on the CDS of non-American countries.

[12] The log return (R) of the index I_i, with $i = 1, 2, \cdots, N$, in the period $t = 1, 2, \cdots, T$ is calculated by means of the following formula:

$$R_{it} = \ln\left(\frac{I_{it}}{I_{it-1}}\right)$$

[13] On average, our unbalanced panel data have 94.5% of non-missing data..

all log return series plus the first difference of the US interest rate are stationary.

Table 2 - CRAs announcement events

Date	Moody's	Standard & Poor's	Fitch Ratings
06/04/2002	B1/Stable		
08/12/2002	B2/Stable		
10/21/2002			B/-
03/10/2003			B/Stable
07/26/2003			BB/Stable
11/06/2003			B+/Stable
09/09/2004	B1/Stable		
01/12/2005	B1/+		
10/11/2005			BB-/+
02/28/2006		BB/Stable	
06/28/2006			BB/Stable
11/22/2006		BB/+	
02/05/2007			BB/+
05/09/2007			BB+/Stable
08/23/2007	Ba1/Stable		
04/30/2008	BBB-/Stable		
07/06/2009	Ba1/+		
11/22/2009	Baa3/+		
06/28/2010			BBB-/+
04/04/2011			BBB/Stable
11/17/2011		BBB/Stable	
06/06/2013		BBB/-	
10/02/2013	Baa2/Stable		
03/24/2014		BBB-/Stable	
09/09/2014	Baa2/-		
04/09/2015			BBB/-
07/28/2015		BBB-/-	
12/09/2015	Baa3/-		
05/05/2016			BB/-
03/15/2017	Ba2/Stable		
05/26/2017	Ba2/-		
08/15/2017		BB/-	
01/11/2018		BB-/Stable	
12/11/2019		BB-/+	
04/06/2020		BB-/Stable	
07/16/2022			BB-/Stable

Source: Country Economy. Prepared by the authors

4 Estimation Results

In Table 3, we present the results regarding the effect of CRA sovereign risk announcements on Ibovespa's return 15 days after the event. We distinguish the effect by rating and outlook/credit watch news to check whether the latter is more effective in changing the stock market's conditions.[14] As Kaminsky and Schmukler's (2002) findings suggested, this might be the case in emerging countries such as Brazil. In addition, our analysis also discriminates the announcements into rating upgrades (outlook/credit watch status improvements) and downgrades (deterioration). In this way, we seek to examine any asymmetric impact such as those reported by the literature.

Table 3 - CRAs announcement effects on Ibovespa return 15 days after the event

Credit News	Outlook and Credit Watch					
Change	Upgrade			Downgrade		
Method	LASSO	GBRT	MLP	LASSO	GBRT	MLP
AAR	0.0024***	0.0022**	0.0023**	-0.0013**	-0.0015*	-0.0013
AAR std	(0.0006)	(0.0008)	(0.0009)	(0.0006)	(0.0008)	(0.0011)
CAR	0.0367	0.0334	0.0346	-0.0193	-0.0229	-0.0188
Credit News	**Rating**					
Change	Upgrade			Downgrade		
Method	LASSO	GBRT	MLP	LASSO	GBRT	MLP
AAR	0.0018***	0.0019**	0.0019*	0.0035***	0.0032***	0.0037***
AAR std	(0.0006)	(0.0008)	(0.0011)	(0.0006)	(0.0008)	(0.0010)
CAR	0.0275	0.0282	0.0289	0.0538	0.0488	0.0568
R-squared	0.6427	0.7563	0.7029	0.6427	0.7563	0.7029

Source: Prepared by the authors. Marginal significance levels: *** denotes 0.01, ** denotes 0.05 and * denotes 0.1. Bootstrap standard errors are in parentheses.

Before we discuss the empirical results, it is important to highlight the ML algorithm's accuracy in the estimation windows. In this sense, Table 3 also reports the R^2 observed in the training set.[15] One can note that the Tree-based approach has the greatest R^2 in the training set, with a value of 75.63%, followed by the Neural Network (70.29%) and the Lasso (64.27%) methods.

Turning to our empirical results, as expected, outlook and credit watch improvement (deterioration) events increase (decrease) the stock market return in the following days after the announcement. Notably, all three ML methods indicate that outlook or credit watch improvements generate an AAR of approximately 0.23%. Regarding the CAR, the average return across all methods suggests an increase of 3,49% in the 15 days after the announcement. On the other hand, two out of three methods agree that outlook and credit watch status deterioration reduces the daily Ibovespa

[14]We group outlook and credit watch status change announcements in one unique event since these credit news have the same economic function, i.e., signalize the direction of a rating change in the near future.

[15]The ML methods have the same R^2 across upgrade and downgrade events because we use all estimation windows to train the ML. Therefore, the training set is the same, independently of the announcement direction.

return by 0.14%, on average. This negative return could produce a devaluation of 2.11% in cumulative terms.

Regarding rating change events, upgrade announcements positively affect Ibovespa returns. This is true for all ML methods applied. Rating upgrades are associated with an AAR of roughly 0.19%, which generates a CAR of around 2.82% in the 15 days following the announcement. Rating downgrade events, however, do not negatively impact the stock market, as expected. On the contrary, all ML methods suggest that rating downgrade announcements are associated with an AAR of approximately 0.35%. In terms of cumulative returns, this AAR could generate a 5.31% increase in market return in the 15 days following the event.

Although not anticipated, the literature has already reported an upward Ibovespa return movement facing a rating downgrade. For instance, Almeida (2010) findings indicate a significant positive AAR on the fourth and seventh days after a rating downgrade of Brazilian bonds. The author argues that investors have already incorporated the rating downgrade event before its announcement into prices and that the rating change would no longer impact the assessment of stock prices. In this sense, investors gradually adjusted their positions to the new market conditions days after the rating downgrade disclosure. Klotzle et al. (2016) found similar results regarding state-owned company stocks. In particular, the CAR of such stocks was around 8,62% in the 10 days following the rating downgrades. We follow this view and assume the positive market response to rating downgrades as investors reacting to market opportunities.

5 Further analysis

Many studies in finance have suggested that investors and financial firms might have access to CRAs' change assessment even before the announcement is publicized. In other words, there is the potential for noisy information in the days before the event, which might deviate market return from some "normal" behavior before CRA's official statement (Castro-Iragorri, 2019). Indeed, Almeida (2010) and Markoski and Moreira (2010) findings confirm this view. Hence, we expand our analysis by checking the presence of abnormal market return 15 days prior to the CRA announcement. Table 4 displays the results.

Table 4 also exhibits the accuracy in the training set of each ML. The R^2 are not the same as in the Table 3 because the training sets are different. Since we changed the event period to 15 days before the official CRA statement, we also modified the training set. Hence, we must train the ML methods again excluding the two weeks data prior to the announcement. As can be seen, the accuracy increased across all methods. Now the Neural Network approach achieved the highest R^2 in the training set (91.90%), followed by the tree-based (79.70%) and the LASSO (70.03%) methods.

Table 4 - CRAs announcement effects on Ibovespa return 15 days before the event

Credit News	Outlook and Credit Watch					
Change	Upgrade			Downgrade		
Method	LASSO	GBRT	MLP	LASSO	GBRT	MLP
AAR	0.0010	0.0014	0.0008	-0.0006	-0.0002	-0.0019
AAR std	(0.0009)	(0.0014)	(0.0014)	(0.0009)	(0.0011)	(0.0013)
CAR	0.0145	0.0212	0.0114	-0.0095	-0.0025	-0.277
Credit News	**Rating**					
Change	Upgrade			Downgrade		
Method	LASSO	GBRT	MLP	LASSO	GBRT	MLP
AAR	0.0015*	0.0013	0.0008	0.0017*	0.0015	0.0025*
AAR std	(0.0009)	(0.0013)	(0.0016)	(0.0009)	(0.0015)	(0.0015)
CAR	0.0232	0.0199	0.0121	0.0251	0.0226	0.0383
R-squared	0.7003	0.7907	0.9190	0.7003	0.7907	0.9190

Source: Prepared by the authors. Marginal significance levels: *** denotes 0.01, ** denotes 0.05 and * denotes 0.1. Bootstrap standard errors are in parentheses.

Regarding the main results of this section, there are no signs of abnormal returns in the two weeks before the official outlook and credit watch status change announcements. This is true independently of the ML method applied. In this sense, this sort of credit news seems to catch the market by surprise, at least in the 15 days before the official event. Otherwise, we would verify any glance of abnormal returns in this period as those found by Markoski and Moreira (2010). One explanation for this result disagreement might be due to differences in the sample period and the statistical approach. Markoski and Moreira (2010) sample covers the period from 1994 to 2003. Besides, the Ibovespa counterfactual is estimated according to the adjusted mean return model, which assumes that the mean return of the market index is constant over time.

In contrast, the results regarding the possibility of leaking information related to rating change statements are inconclusive. In upgrade scenarios, the LASSO method points out an AAR of 0.15%, which could generate a CAR of 2.32% two weeks before the official announcement. Nevertheless, according to the GBRT and MLP methods, there is no sign of abnormal returns. Concerning downgrade situations, we found mixed results. The LASSO and MLP methods indicate a statistically significant AAR of 0.21% on average, which could generate a CAR of 3.17%. Again, albeit counterintuitive, this positive relationship aligns with what we observed in the analysis of the latter section. The GBRT, however, suggests no evidence of AAR in the days before the official CRA statement.

6 Conclusions

By indicating a country's likelihood of default, CRAs' sovereign risk assessments play a fundamental role in attracting international capital, especially in developing countries. In turn, changes in CRAs' appraisals can trigger substantial changes in the restructuring of international portfolios. These capital movements might affect the stock market, particularly during the days following CRAs' official disclosure. In this sense, this work investigates the impact of CRAs' credit risk change announcements regarding Brazilian bonds on the local stock market. In particular, we check the presence of abnormal returns within 15 days before and after these events.

Our analysis considers 36 announcements regarding rating and outlook/credit watch status changes from 2002 to 2022. Furthermore, we examine potential asymmetric effects related to upgrade and downgrade events. We followed the finance literature by adopting an event study approach. However, instead of relying on a mean-adjusted model to construct the stock market counterfactual as is usually done, we applied the ArCo method developed by Carvalho et al. (2018). This method fits into our research once no control group is available when a CRA discloses a change in its assessment of the Brazilian likelihood of default, which can be considered a treatment in the ArCo methodology.

Our findings indicate that both rating and outlook/credit watch status change announcements alter the short-run return path of the Ibovespa index. In particular, the effects of outlook and credit watch improvement events are more potent than their rating equivalents. On the other hand, downgrade episodes might alter market conditions in the opposite direction, depending on whether a rating or outlook change announcement was made. An outlook (rating) downturn event reduces (increases) the stock market return. The inverse relationship between sovereign risk perception and stock market return in the days following a rating downgrade announcement had already been found in the literature that studied the Brazilian case (e.g., Almeida, 2010). We interpret this counterintuitive result as investors reacting to market opportunities. In addition, there are no signs of abnormal returns two weeks before the official outlook and credit watch status change announcements. In contrast, the results regarding the possibility of leaking information related to rating change statements are inconclusive. These results might be of great interest to market agents in general, particularly retail investors.

We must emphasize that our conclusions are limited to a specific event window. For this reason, a natural suggestion for future research is to consider different event windows beyond the 15 days contemplated by this study. By taking into account shorter time periods, such as 1, 3, or 5 days, one can verify hidden patterns not observed in this study. Another research agenda would be to examine the effect of CRA announcements on stock market volatility. This task can also be performed by applying the ArCo method and relying on the same peer group used in this study.

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Appendix - A1

We briefly describe each ML algorithm applied in this study based on Hastie et al. (2009). In order to do so, consider that the data consists of $j = 1, 2, \cdots, p$ inputs (covariates) and their associated outputs (outcomes) for each T observations, i.e.,

(x_t, y_t) for $t = 1, 2, \cdots, T$ being the time index, with $x_t = (x_{t1}, x_{t2}, \cdots, x_{tp})$ being a vector of inputs belonging to each period t.

A1.1. LASSO. The Lasso is a linear regression method that performs variable selection and regularization to enhance the prediction accuracy and interpretability of the resulting statistical model. The lasso method assumes that the coefficients of the linear model are sparse, meaning that few of them are non-zero. The Lasso coefficients $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \cdots, \hat{\beta}_p)$ are those that solves the following problem:

$$\hat{\beta} = \underset{\beta}{argmin} \left\{ \frac{1}{2} \sum_{t=1}^{T} \left(y_t - \beta_0 - \sum_{j=1}^{p} x_{tj}\beta_j \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{11}$$

where $\lambda > 0$ is the regularization parameter that seeks to shrink the coefficients towards zero. As can be noted, selecting an adequate value of λ is critical; therefore, the grid-search cross-validation procedure is fundamental for this task.

A1.2. Gradient Boosted Trees. Tree-based ML methods partition the feature space into a set of mutually exclusive groups and then fit a model in each one of them. Essentially, they learn a hierarchy of if/else questions that lead to a decision. This is achieved through a growing tree structure, where each node (group) is split using the best split possible among all input variables. The algorithm decides the splitting variables, their split points and the shape the tree should have. In this sense, consider that we have a partition of the feature space into M regions $R_1, R_2, \cdots, R_M$, where the prediction will be given by a constant c_m in each region:

$$\hat{y}_t(x_t) = \sum_{m=1}^{M} c_m I(x_t \in R_m) \tag{12}$$

One can show that if the criterion of minimization given by the residual sum of squares is chosen, the best $\hat{c}_m$ is the average of y_t in region R_m:

$$\hat{c}_m = ave(y_t | x_t \in R_m) \tag{13}$$

Since finding the best binary partition in terms of the sum of squares is computationally infeasible, another algorithm is proposed. Starting with all of the data, suppose a splitting variable j and split point s and define the pair of half-planes such as:

$$R_1(j, s) = \{x | x_j \leq s\} \quad and \quad R_2(j, s) = \{x | x_j > s\} \tag{14}$$

Then, the goal is to split variable j at the split point s that solves:

$$\min_{j,s} \left[\min_{c_1} \sum_{x_t \in R_1(j,s)} (y_t - c_1)^2 + \min_{c_2} \sum_{x_t \in R_2(j,s)} (y_t - c_2)^2 \right] \tag{15}$$

For any choice of j and s, the inner minimization is solved by:

$$\hat{c}_1 = ave(y_t|x_t \in R_1(j,s)) \quad and \quad \hat{c}_2 = ave(y_t|x_t \in R_2(j,s)) \tag{16}$$

Once the best split is determined, the data is partitioned into two resulting regions and then the process is repeated in each of these new regions and so on.

The GBRT is an ensemble method combining many different decision trees to create a more robust model. In particular, this method works by serially building trees so that each tree can correct mistakes committed by the previous one. The idea behind this type of tree-based model is to combine many simple models, like shallow trees, and then make the overall prediction based on a weighted average of the predictions of several different trees. Those trees that made accurate predictions on the training data receive a greater weight than those that performed poorly. The main parameter that must be fit is the rate at which a tree learns from the mistakes of the previous one.

A1.3. Multilayer Perceptron. The MLP regression is part of a family of algorithms inspired by biological neural networks. This method is usually viewed as generalizations of linear models that execute several layers of estimation, each with multiple parameters (weights), before coming to a prediction. A back-propagation technique calculates the error between the output and predicted values. It provides feedback on the error information through the whole network to each neuron in each layer so that weights can be modified to minimize the residual sum of squares. Two important parameters must be set to enable learning: the learning rate and the momentum. The first refers to the rate at which errors adjust the weights associated with each neuron in each layer. The latter determines that if the weight is modified to a certain direction, it will likely keep changing in that direction (Ozturk et al., 2016).

Formally, consider the output provided by the nth neuron in the lth layer given by:

$$z_n^l(t) = \varphi\left[\sum_{\gamma=1}^{\Gamma} w_{n\gamma}^l(t) z_\gamma^{l-1}(t) + \psi_n^l\right] \tag{17}$$

where $\varphi(\cdot)$ is the activation function, which is the Rectified Linear Unit (ReLU) in this study; $l = 1, 2, \cdots, L$ is the number of layers in the network; $n = 1, 2, \cdots, N$ is the number of neurons in the layer l; $\gamma = 1, 2, \cdots, \Gamma$ is the number of neurons in the layer $l-1$; $w_{n\gamma}^l$ is the weight that connects neuron n in layer l with a neuron γ in the preceding layer $l-1$; and ψ is a bias that captures the intercepts. Therefore, the output provided by the nth neuron in the first layer is defined as:

$$z_n^1(t) = \varphi\left[\sum_{\gamma=1}^{\Gamma} w_{n\gamma}^1(t) z_\gamma^{l-1}(t) + \psi_n^1\right], \quad since \quad z_n^0(t) = x_j(t) \tag{18}$$

For an l-layer network, the synaptic weight $w_{n\gamma}^l(t)$ is updated by:

$$w_{n\gamma}^l(t+1) = w_{n\gamma}^l(t) + \Delta w_{n\gamma}^l(t) \tag{19}$$

where $\Delta w_{n\gamma}^l(t)$ is the gradient that calculates the marginal effect of input x_j on the residual sums of squares. Finally, the predicted output is given by a linear weighted combination of all the outputs from the last layer plus an intercept:

$$\hat{y}_t(x_t) = \sum_{\gamma=1}^{\Gamma} w_{n\gamma}^L(t) z_\gamma^{L-1}(t) + b \tag{20}$$

Appendix - A2

Table A1 - Grid-search cross validation results

Hyperparameters	Training set	
	$[t_0$ - 31, t_0 - 1]	$[t_0$ - 31, t_0 - 16]
	LASSO	
Alpha	0.01	0.01
Intercept	False	False
Selection	Random	Random
	GBRT	
Loss function	Squared Error	Squared Error
Learning rate	0.1	0.1
N estimators	100	64
Max depth	2	2
Min samples split	9	7
Min samples leaf	1	3
Max features	30	44
	MLP	
Solver	SGD	SGD
Activation	ReLU	ReLU
N layers	2	2
Hidden layer sizes	(90, 70)	(80, 50)
Alpha	0.99	0.99
Learning rate	Adaptive	Adaptive
Initial learning rate	0.001	0.001
Momentum	0.5	0.9

Source: Prepared by the authors

Table A2 - Dependent variable and peer group data source

Country	Ticker	Source	Country	Ticker	Source
Australia	ASX	Investing	Mexico	MEXBOL	Investing
Belgium	BEL 20	Investing	Morocco	MASI	Investing
Botswana	BSE	Investing	Netherlands	AEX	Investing
Brazil	IBOV	Brazil Stock Exchange	New Zealand	NZ50	Investing
Canada	TSX	Investing	Pakistan	KSE	Investing
China	SSE	Yahoo Finance	Philippines	PSEi	Yahoo Finance
Croatia	CROBEX	Investing	Poland	WIG	Investing
Czech Republic	PX	Investing	Russia	IMOEX	Investing
Denmark	OMX	Investing	Saudi Arabia	TASI	Investing
Estonia	OMXTGI	Investing	Slovakia	SAX	Investing
Finland	OMXH25	Investing	South Africa	JALSH	Investing
France	CAC	Investing	South Korea	KOSPI	Investing
Germany	DAX	Investing	Spain	IBEX35	Investing
Global	BCOM	Investing	Sri Lanka	CSE	Investing
Hungary	BUX	Investing	Sweden	OMXS30	Investing
Iceland	OMXIPI	Investing	Switzerland	SSMI	Investing
Indonesia	JKSE	Yahoo Finance	Thailand	SETI	Investing
Japan	TOPX	Investing	Tunisia	TUNINDEX	Investing
Kazakhstan	KASE	Investing	Turkey	XU100	Investing
Latvia	OMXRGI	Investing	United Kingdom	FTSE	Investing
Lithuania	OMXV	Investing	United States of America	NYA	Investing
Malta	MSE	Investing	US Effective Federal Funds Rate	EFFR	Federal Reserve Bank of St. Louis
Mauritius	MDEX	Investing	Vietnam	VNI	Investing

Source: Prepared by the authors

Table A3 - Descriptive statistics

Index	ASX	BEL 20	BSE	IBOV	TSX	SSE	CROBEX	PX	OMX	OMXTGI	OMXH25	CAC	DAX	BCOM	BUX	OMXIPI
Observations	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620
Mean	0.0000	0.0000	0.0003	0.0002	0.0000	0.0005	0.0002	0.0001	0.0004	0.0002	0.0001	-0.0001	-0.0001	-0.0002	0.0003	0.0005
Std. Deviation	0.0108	0.0137	0.0047	0.0182	0.0115	0.0164	0.0122	0.0123	0.0120	0.0104	0.0135	0.0155	0.0161	0.0100	0.0144	0.0092
Minimum	-0.1020	-0.1533	-0.0420	-0.1599	-0.1318	-0.1088	-0.1073	-0.0816	-0.0782	-0.1060	-0.1068	-0.1310	-0.1305	-0.0460	-0.1227	-0.0788
Q1	-0.0047	-0.0052	-0.0003	-0.0083	-0.0041	-0.0060	-0.0036	-0.0050	-0.0053	-0.0032	-0.0063	-0.0065	-0.0067	-0.0053	-0.0068	-0.0030
Q2	0.0002	0.0002	0.0000	0.0011	0.0002	0.0000	0.0000	0.0002	0.0004	0.0001	0.0003	0.0000	0.0006	0.0000	0.0000	0.0002
Q3	0.0052	0.0061	0.0009	0.0101	0.0050	0.0075	0.0044	0.0064	0.0067	0.0041	0.0070	0.0070	0.0073	0.0054	0.0075	0.0047
Maximum	0.0677	0.0933	0.0820	0.1302	0.1129	0.1274	0.1140	0.0737	0.0497	0.1209	0.0666	0.0806	0.1041	0.0482	0.0563	0.0401

Index	JKSE	TOPX	KASE	OMXRGI	OMXV	MSE	MDEX	MEXBOL	MASI	AEX	NZ50	KSE	PSEi	WIG	IMOEX
Observations	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620
Mean	0.0001	-0.0004	0.0010	0.0004	0.0007	0.0001	0.0005	0.0002	0.0001	0.0000	0.0004	0.0007	0.0004	-0.0002	0.0005
Std. Deviation	0.0132	0.0136	0.0289	0.0125	0.0101	0.0071	0.0080	0.0119	0.0086	0.0155	0.0074	0.0138	0.0123	0.0150	0.0180
Minimum	-0.1093	-0.1058	-0.4864	-0.1634	-0.0667	-0.0454	-0.1010	-0.0664	-0.0923	-0.1138	-0.0795	-0.0774	-0.1508	-0.1425	-0.1048
Q1	-0.0052	-0.0063	-0.0048	-0.0043	-0.0025	-0.0025	-0.0016	-0.0057	-0.0027	-0.0066	-0.0031	-0.0047	-0.0051	-0.0075	-0.0069
Q2	0.0002	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0004	0.0005	0.0004	0.0000	0.0000	0.0000
Q3	0.0065	0.0066	0.0058	0.0050	0.0039	0.0025	0.0025	0.0061	0.0037	0.0067	0.0041	0.0077	0.0061	0.0074	0.0098
Maximum	0.0701	0.0773	0.4876	0.1209	0.1093	0.0677	0.1027	0.0712	0.0531	0.0952	0.0694	0.0913	0.0720	0.0634	0.1015

Index	TASI	SAX	JALSH	KOSPI	IBEX35	CSE	OMXS30	SSMI	SETI	UNINDEX	XU100	FTSE	NYA	EFFR	VNI
Observations	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620	1620
Mean	0.0002	0.0004	0.0002	0.0004	-0.0001	0.0008	0.0000	0.0000	0.0003	0.0002	0.0005	0.0000	0.0000	0.0008	0.0003
Std. Deviation	0.0126	0.0105	0.0126	0.0130	0.0144	0.0103	0.0145	0.0123	0.0128	0.0106	0.0183	0.0125	0.0128	0.0663	0.0135
Minimum	-0.1023	-0.0958	-0.1023	-0.0877	-0.1515	-0.1389	-0.1117	-0.1013	-0.1606	-0.2669	-0.1117	-0.1151	-0.1260	-0.8500	-0.0806
Q1	-0.0056	-0.0024	-0.0056	-0.0046	-0.0063	-0.0025	-0.0066	-0.0053	-0.0040	-0.0019	-0.0082	-0.0047	-0.0046	-0.0100	-0.0053
Q2	0.0000	0.0000	0.0000	0.0003	0.0003	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0001	0.0003	0.0000	0.0000
Q3	0.0066	0.0037	0.0066	0.0069	0.0070	0.0041	0.0071	0.0058	0.0059	0.0024	0.0098	0.0056	0.0054	0.0100	0.0064
Maximum	0.0905	0.0545	0.0905	0.0825	0.0753	0.1162	0.0884	0.0678	0.1058	0.2654	0.1180	0.0867	0.0956	0.7500	0.0733

Source: Prepared by the authors

Table A4 - ADF unit root test results

Index	ASX	BEL 20	BSE	IBOV	TSX	SSE	CROBEX	PX	OMX	OMXTGI	OMXH25	CAC	DAX	BCOM	BUX	OMXIPI
Equation	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T
Lag	11	11	12	6	7	2	2	0	0	11	0	10	11	4	1	10
t-stat	-10.526	-11.341	-7.855	-14.041	-13.940	-23.451	-21.322	-38.425	-39.104	-9.252	-38.014	-13.111	-11.412	-19.286	-27.367	-11.625
10%	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129

Index	JKSE	TOPX	KASE	OMXRGI	OMXV	MSE	MDEX	MEXBOL	MASI	AEX	NZ50	KSE	PSEi	WIG	IMOEX
Equation	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T
Lag	0	0	2	4	9	5	12	7	3	9	1	12	10	0	9
t-stat	-38.413	-40.491	-28.428	-19.002	-10.173	-13.572	-12.849	-15.698	-20.200	-14.151	-24.473	-10.307	-12.507	-38.727	-14.500
10%	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129

Index	TASI	SAX	JALSH	KOSPI	IBEX35	CSE	OMXS30	SSMI	SETI	TUNINDEX	XU100	FTSE	NYA	EFFR	VNI
Equation	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T	I/T
Lag	7	0	7	5	4	12	6	8	5	1	0	9	10	12	12
t-stat	-14.886	-44.962	-14.886	-17.639	-18.201	-9.956	-15.785	-14.894	-16.464	-34.695	-41.678	-14.203	-11.381	-9.252	-9.184
10%	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129	-3.129

Source: Prepared by the authors. The final choice of lag was made based on the Akaike criterion. "I" denotes intercept; "I/T" denotes intercept and trend; and "N" denotes none.