Assessment of informed trading in the Brazilian equity market: Market cleanliness methodology

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Abstract

This study extends prior work on the measurement of informed trading to the Brazilian equity market. The quantitative analysis employed two market cleanliness methodologies that have been widely applied in academic and regulatory research and that could be replicated using public data. The analysis advances our understanding of Brazil's capital market integrity, provides a baseline for assessment of new regulation or regulatory practices and supplies more information for the regulator and investor's decision-making process. The key intuition behind the methodologies is supported by the efficient markets hypothesis which claims that new information should immediately be converted into price changes. By examining significant price movements ahead of companies' disclosures, the methodologies seek to measure the "cleanliness" of the market. The findings from this research suggest that levels of informed trading measured using Brazil's data were higher than the values obtained in similar studies using the United Kingdom's and Australia's data. The Securities and Exchange Commission of Brazil introduced a strategic project focused on primary insider trading during late 2015, and there are signs that informed trading has decreased from 2015 to 2016. However, in order to properly evaluate the impact of the project, future measurements of informed trading are still necessary.

Keywords: Market cleanliness, informed trading, securities regulation, event study, insider trading, open data

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Disclamer

The views and opinions expressed in this thesis are those of the author and do not necessarily reflect the official policy or position of any Brazilian government bodies or the University of Tokyo. The assessment was based only on public data. No sensitive information stored or generated by the Securities and Exchange Commission of Brazil was used for the analysis performed within this thesis. Assumptions made within the analysis do not reflect the position of any Brazilian government entity.

The material and information contained on this study are for general information purposes only and should not be used for making business, legal or any other decisions. Whilst I sought to provide true and complete information to the best of my knowledge, any reliance placed on the information or recommendations is strictly at your own risk.

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1 Introduction

Before discussing the methodologies employed in this study, it is important to understand the consequences of having impaired market integrity and the challenges faced by securities regulators to address this issue.

If investors consider the market environment as unfair or perceive they are in a disadvantageous position, they tend to become more protective and conservative about their investment decisions. Without trust and confidence, investors reduce their participation and exposure in the market and demand higher returns, which may lead to higher transaction costs, diminish funding availability, lower liquidity, create financial instability, produce inefficient allocation of capital in the economy and lower economic growth.

Effective misconduct supervision and enforcement are key factors to holding individuals and entities accountable, deterring illegal activities, and promoting market discipline. This prevents the corrosive effects caused by impaired market integrity, boosting investors' confidence, improving market efficiency, and fostering resilient institutions and economies.

Countries organize their financial regulatory activity in different ways. According to Carvajal and Elliott (2009),"there are three essential elements of securities regulation: the legal framework, the supervision program, and the enforcement program." Supervision seeks to foster compliance with the legal framework in order to prevent misconducts and also monitor market participants to detect non-compliances. "Enforcement is an ex-post tool used to punish breaches of laws and regulations as well as to deter future wrongdoings."

Even though market supervision and enforcement play a crucial role in providing a fair and efficient market environment, they are most challenging for regulators. Compared to the financial industry, the huge salary, technology, and provision gaps expose regulators to shortages of skilled personnel and to a lack of appropriate tools for maintaining effective supervision and enforcement programs. In addition, inspections, investigations, and enforcement actions are time-consuming and resource-intensive. Regulators have the burden of proof, and as enforcement cases can potentially impose high financial losses, stakes are even higher.

The development of data mining techniques has greatly expanded in the last few years and could be used to bring down the cost of regulatory tools. Data mining is a powerful tool to process large information datasets, and it has impacted a few areas of the capital markets such as risk analytics and market surveillance not only for regulators but also for financial market participants.

The size of today's databases is measured in terabytes. The huge amount of data available for regulators may contribute to detecting market abuse. However, the ability to interpret such a large volume of data and produce substantive information that can be used to support supervision and enforcement action still represents a difficult challenge.

Given the significance of market integrity for the economy and the detrimental effects created by the occurrence of unfair market practices like insider trading, securities market regulators in countries such as the United Kingdom and Australia have developed data mining techniques to measure the level of informed trading, as shown in Dubow and Monteiro (2006), ASIC (2016), and Monteiro et al. (2007). They proposed what was denominated as "market cleanliness" methodologies to measure how often there are significant stock price movements ahead of the disclosure of new information by public traded companies in order to estimate the fairness of the market conditions.

The methodologies can also be applied to assess the impact of changes in legislation or regulatory activity. Dubow and Monteiro (2006) and Monteiro et al. (2007) examined changes in the United Kingdom's market after the introduction of the Financial Services and Markets Act (FSMA) in 2001 and FSMA's enforcement actions after 2004.

The fundamental intuition for the measurement of market cleanliness is that in an efficient market "prices adjust quickly and, on average, without bias, to new information," as explained by Clarke et al. (2001). Therefore, in a clean market, where all information is publicly available at the same time, prices should react immediately after announcements from issuing firms. On the other hand, if prices move ahead of announcements, it indicates inefficiencies and possibly unfair behavior of market participants or investors.

Assessing informed trading using data mining techniques can be valuable for supervision and enforcement activities from securities regulators. These techniques can be cost-effective tools for evaluating the overall behavior of the market, providing timely information for the supervision and investigation, assigning priorities to focus efforts, and analyzing the impact of changes in regulation or enforcement deterrence effects. Moreover, they provide information to investors to better understand market risks and conditions.

This study aims to estimate informed trading by applying different methodologies to Brazil's data. Current policies implemented by the securities regulator are examined for they impact over informed trading measurement results.

Measurements of the level of informed trading could be used to assess the impact of the changes in regulatory practices on market behavior and deterrence. Although there have not been significant changes in Brazilian securities regulations regarding insider trading and listed companies' disclosure since 2001, there were changes in terms of enforcement of regulations as described below.

According to the Securities and Exchange Commission of Brazil (CVM) annual reports, the CVM expanded the workforce in charge of market surveillance and enforcement and at the end of 2014 approved a strategic project ("Regime Sancionador II: foco Insider") to improve its detection and enforcement capabilities of insider trading activities. After 2014, CVM was able to analyze all trades performed by parent companies, issuer firms, and firms' administrators during the blackout period.

Throughout 2015, the commission constituted an interdepartmental work group, reviewed its supervision, inspection and enforcement performance regarding insider trading as well as past cases, self-regulator procedures, and specialists opinions. Thereafter, it conducted a survey of best practices among overseas regulators. As a result, an improvement plan was scheduled to start by the end of 2015 and continue through 2016. The plan mainly focused on primary insider, i.e. a person who possesses inside information by virtue of his position, employment or responsibilities. Secondary insiders, on the other hand, obtain information from another person who possesses privileged information.

Moreover, one of the motivations for choosing these methodologies was that the analysis can be done entirely with publicly available data. This encourages public participation which could be a useful source of information and intelligence to identify misconduct and helps to ameliorate some incentive distortions. Disseminating the information of companies whose stocks are prone to present informed trading should create incentives for financial institutions to improve practices regarding sensitive information.

The CVM has published an Open Data Plan in 2016 to expand and guide the publication of information by the CVM in order to facilitate citizens' access and contribute to information sharing among other public organizations. It includes data generated or received by the Commission that is not protected by secrecy laws or regulations and its main objectives are: identify and prioritize the access to information according to citizens' priorities, promote social participation and empowerment, improve the quality and timeliness of data provision, enhance transparency, and encourage innovation and sustainable development of initiatives.

This study offered an opportunity to examine the availability of the data employed in this type of measurement. According to the Open Definition Project, "open means anyone can freely access, use, modify, and share for any purpose." In order to fully enjoy the benefits of open data, it is imperative to examine the usability of the data, since bad open data implementation increases the cost, in its broad sense, of accessing and interpreting the information, discouraging its use and crippling all positive impacts that could result from an open data initiative.

The purpose of this study is to evaluate the feasibility of applying two methodologies to detect informed trading activity to Brazilian equity market data, to analyze the methodologies and their results over time, and to evaluate the impact of the regulators' efforts for improving insider trading detection and enforcement.

This work is structured as follows. This section provides the background and basic conceptual framework of market cleanliness. Section 2, which is the main section of this paper, describes the two methodologies employed for the assessment of informed tradings and their results. The conclusion, in section 3, considers two policy recommendations and suggestions for future research.

1.1 Market cleanliness

Data mining techniques in market surveillance are employed to create misconduct behavior models, extract information based on the analysis of past activities, and detect possible patterns that can be used for supporting the decision-making process, but they are not a solution by themselves.

A quantitative method to measure informed trading was proposed by Dubow and Monteiro (2006), in an occasional paper published by the United Kingdom's Financial Services Authority (FSA), currently known as Financial Conduct Authority (FCA). They estimated the market cleanliness level as an indicator of market inefficiencies and possible unfair practices by measuring the level of significant stock price movements ahead of the disclosure of new information. This method was later updated by Monteiro et al. (2007) and adapted for the measurement of market cleanliness in the Australian equity market by ASIC (2016).

It is important to highlight that the name "market cleanliness" is somewhat counter-intuitive. Although it is used to estimate how "clean" the market is, the higher the level of market cleanliness measured, the less clean the market is. For this reason, I prefer to refer to the results as measurements of informed trading.

The method is based on the efficient markets hypothesis (EMH). Clarke et al. (2001) propose that "if markets are efficient and security prices reflect all currently available information, new information should rapidly be converted into price changes." The rationale is that stock price only effectively changes as a response to new information.

The idea behind the market cleanliness methodology is that if price movements ahead of the publication of new information were substantially large and in the right direction, it suggests that markets are not operating efficiently. Possible explanations for this behavior points to the occurrence of unfair practices such as insider trading activity or information leakage from the company. A high measurement of informed trading provides only an indication of uneven market conditions but does not necessarily confirm that any wrongdoing has taken place. There are also other factors that do not constitute misconducts that could cause similar effects such as prices reacting to investors expectations, rumors or demand-supply imbalances.

Figure 1 describes the main intuition behind how insider trading might affect prices and some elements needed for market cleanliness calculation.

In a clean and efficient market, described by the blue dashed line, prices returns should follow a pattern in the absence of new information, which can be captured by a statistical model estimated over the estimation window period. This statistical model can be used to forecast stock prices after the estimation window period (black dashed line).

After an event, characterized by a public announcement containing new information, this information becomes publicly available at the same time for all market participants. As a result, prices should react immediately causing a significant change in stock prices in respect to the expected asset price. For positive news, prices should increase as in “Situation 1.” On the other hand, if the market interprets the news as being negative for the firm’s value, prices will decrease as in “Situation 2.”

If new information is leaked to investors before the public announcement and insider trading occurs, asset prices may be affected during the pre-event window and in the same direction as the overall price change of the event window, situation described by the red solid line from figure 1. Therefore, by measuring this behavior, we can estimate the incidence of informed trading in the market.

According to MacKinlay (1997), event studies can be used to estimate the effect of an event on the value of a firm, which in this case is the impact of the arrival of new information measured on stock price returns. The first step for performing an event study is defining when the events have occurred.

Listed companies are obligated to disclose all information that might affect their share’s value. Therefore, those announcements can be used as a proxy for the events. However, not all announcements consist of new information. To analyze the impact of stock prices on new information, we need to determine which of the announcements really contain new and material information. Therefore, we must classify the announcements as significant or not. Significant announcements will be treated in the analysis as those containing new information that affects the value of the firm.

In this event study, the event window and pre-event window are the periods over which the impact of the event and the informed trading activity are analyzed, respectively. Note that the event window must contain the day of the event and include the price change for both the clean and unclean market situations. The pre-event window must be located before the event day and should include the period when the informed trading activity is expected to have taken place. According to Brooks (2014), “it is common to examine a period comprising, say, ten trading days before the event up to ten trading days after as a short-run event window.”

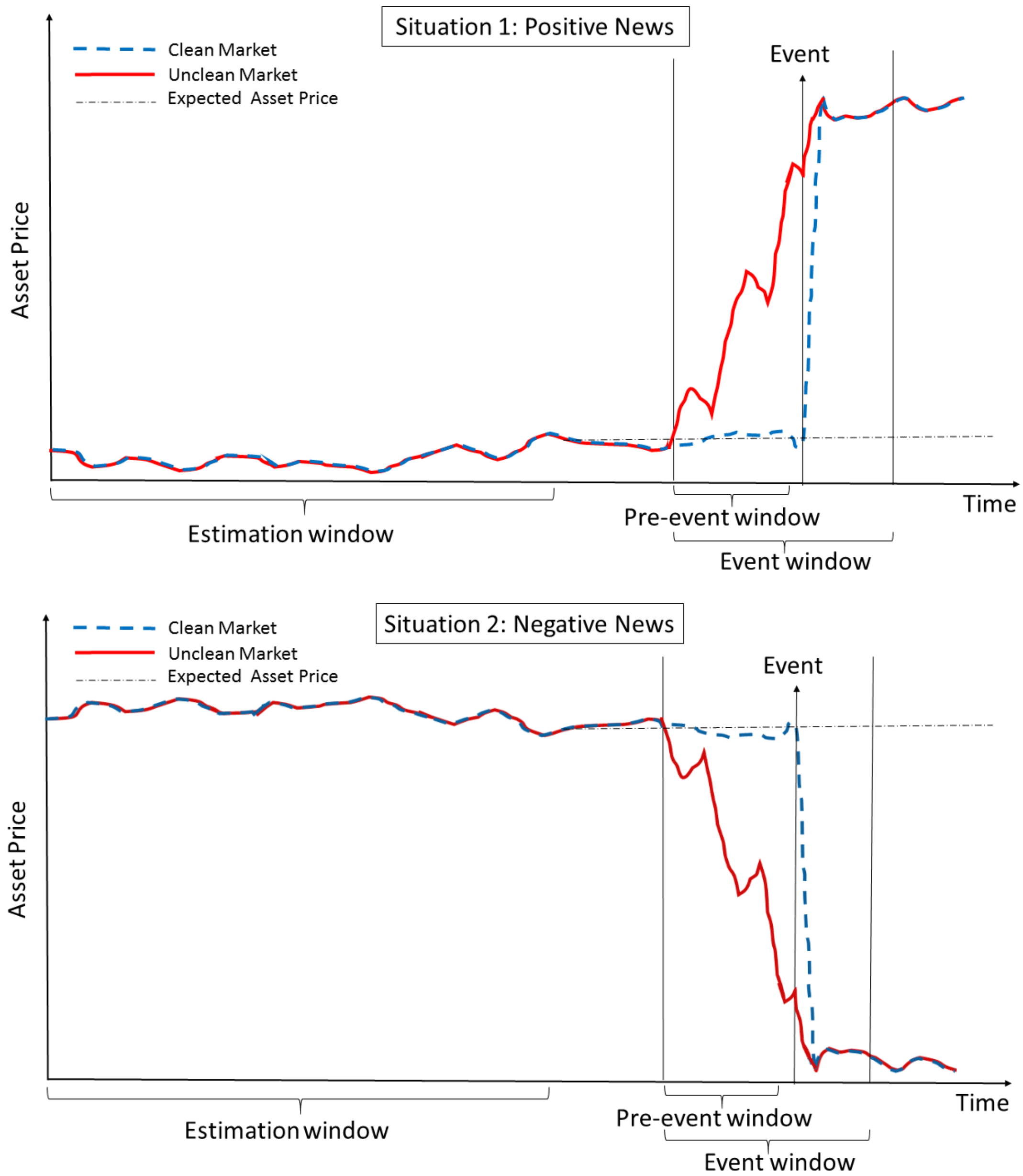


Figure 1 – Key concepts of Market Cleanliness

To estimate the parameters of the statistical model, a sample of data from a period before the event (estimation window) is utilized. The methodology assumes that, during the estimation window, asset prices behave "normally" and are not influenced by any significant news or change in performance compared to the event and pre-event periods except by the impact caused by the event. Brooks (2014) suggests a sample of 100 to 300 daily observations, as "longer estimation windows will in general increase the precision of parameter estimation, although with it the likelihood of a structural break and so there is a trade-off."

The objective of this event study is to measure the effects of a significant announcement on stock price returns. Asset price daily returns can be calculated using the arithmetic returns (1) or logarithmic returns (2), using prices ($P_{i,t}$) from security i on trading day t.

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{1}$$

$$R_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{2}$$

In order to know if the behavior of returns changed significantly during the event window, we need to compare it with the expected behavior of the stock price returns. This is the reasoning behind the use of abnormal returns (AR_{it}) which are defined as the difference between the actual return (R_{it}) of a stock i on day t and the respective expected return ($E(R_{it})$) calculated using the statistical model.

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{3}$$

The distribution of abnormal returns should be asymptotically normally distributed and with zero mean and variance σ^2 ($AR_{it} \sim N(0, \sigma^2(AR_{it}))$. For a standardized abnormal return, we can divide the abnormal returns by their standard errors, resulting in an asymptotically standard normal distribution, as shown in (4).

$$SAR_{it} = \frac{AR_{it}}{\sqrt{\hat{\sigma}^2 (AR_{it})}} \sim N(0, 1) \tag{4}$$

Since the stock returns vary a lot over the days in the event window, the abnormal returns can be aggregated over time to test the significance of the entire event window. The same logic can be applied to the pre-event period.

When using arithmetic returns, the aggregated abnormal return is calculated using the buy-and-hold abnormal return ($BHAR_i$) (6). On the other hand, when using logarithmic returns, cumulative abnormal return (CAR_i) (5) is employed to calculate the aggregated value over the period $(t_1, \ldots, t_2)$.

$$^{(t_1,t_2)}CAR_i = \sum_{j=t_1}^{t_2} AR_{i,j} \tag{5}$$

$$^{(t_1,t_2)}BHAR_i = \left[\prod_{j=t_1}^{t_2} (1 + R_{ij}) - 1\right] - \left[\prod_{j=t_1}^{t_2} (1 + E(R_{ij})) - 1\right] \tag{6}$$

Finally, a hypothesis test can be used to determine whether there is enough evidence to infer that the abnormal returns over the event window of length k (cumulative average return of the period) have been affected by the event and the price change is significantly different from the expected value calculated from the estimation window. Under the null hypothesis (7), the event had no influence over the stock prices of the period. If we test the event window and reject the null hypothesis, we can classify the event as significant which implies that the announcement from the company contains new information (8).

$$H_0 : \; E\left({}^{k}CAR_{i,(estimation\,window)}\right) = {}^{k}CAR_{i,(event\,window)} \tag{7}$$

$$H_1 : \; E\left({}^{k}CAR^{k}_{i,(estimation\,window)}\right) \neq {}^{k}CAR_{i,(event\,window)} \tag{8}$$

After that, for all significant announcements (SA), another hypothesis test must by performed for evaluating the significance of the pre-event window of length k'. By rejecting the null hypothesis (9), we can conclude that significant price movements ahead of the announcement have occurred, alternative hypothesis (10). If those pre-event price movements are in the same direction of the overall event prices, it suggests that informed trading has taken place and it will be classified as an informed price movements (IPM).

$$H_0 : \; E\left({}^{k'}CAR_{i,(estimation\,window)}\right) = {}^{k'}CAR_{i,(pre-event\,window)} \tag{9}$$

$$H_1 : \; E\left({}^{k'}CAR_{i,(estimation\,window)}\right) \neq {}^{k'}CAR_{i,(pre-event\,window)} \tag{10}$$

It is necessary to point out that this approach assumes the absence of window clustering. That is, no overlap of the event windows of a security over different events. The same applies for pre-event windows. This is necessary to obtain independent aggregate abnormal returns which are needed for the inference procedures described.

The market cleanliness index is calculated by "the proportion of significant announcements where the announcement is preceded by an IPM," as explained by Dubow and Monteiro (2006) and can be expressed by the (11).

$$Market\ cleanliness\ index = \frac{\sum informed\,price\ movement\ (IPM)}{\sum significant\ announcement\ (SA)} \tag{11}$$

Even though market cleanliness measurements provide a reasonable indicator of market inefficiencies, there are some limitations to the methodology. Agents involved in insider trading practices try to minimize their impact on prices in order to maximize profits and keep a low profile. Unfortunately, if there are no significant changes in prices, market cleanliness methodology cannot detect the occurrence of informed trading. In addition, if the insider trading activity did not take place during the pre-event window, it will not be identified by this methodology.

There are some controversies regarding the impact of algorithmic trading on market cleanliness measurements. Monteiro et al. (2007) suggested that it "may contribute to a weaker link between insider trading and equity prices, allowing insiders to more easily disguise their trades and minimize their impact on prices." On the other hand, ASIC (2016) pointed out that "high-frequency traders may become more adept at detecting the risk of adverse selection from traders with potentially superior information from order flow changes, which may exacerbate their price impact."

Regardless of its limitations, the market cleanliness methodology can provide the Brazilian regulator and investors with a comprehensive measure of informed trading over time.

2 Methodological Design

In this study, the Brazilian equity informed trading level was measured using two different methods that have been largely applied in other academic and regulatory publications. The same data was used in both methodologies in order to evaluate differences and compare results.

The first methodology to estimate informed trading labeled "Method A" was published by the United Kingdom's Financial Services Authority (FSA), Dubow and Monteiro (2006). A similar version with a different sized pre-event window was also used in ASIC (2016), a report published by the Australian Securities & Investments Commission.

Method A uses simple linear regression to model stock returns and make inferences about abnormal behavior using quantile thresholds from an unconditional bootstrap distribution. This method is described in Subsection 2.2 and the mathematical specification was detailed in Subsections 2.2.1 and 2.2.2.

The second methodology labeled "Method B" attempts to replicate the process proposed by Monteiro et al. (2007) and published by the FSA. This methodology tries to account for the presence of serial correlation and heteroskedasticity and uses quantile thresholds from a conditional bootstrap distribution for the hypothesis test.

Method B uses either simple linear regression (LR), autoregressive distributed lag (ADL), linear regression with generalized autoregressive conditional heteroskedasticity (LR-GARCH) or autoregressive distributed lag with generalized autoregressive conditional heteroskedasticity (ADL-GARCH) to model stock returns. This method is described in subsection 2.3 and the mathematical specification was detailed in subsection 2.3.1.

Both methodologies and their results were compared in subsection 2.4. The measurements were also used to evaluate the impact of the strategic project to improve supervision, inspection and enforcement performances regarding insider trading from the Securities and Exchange Commission of Brazil (CVM). The project's procedures were scheduled to start by late 2015 and continue throughout 2016.

2.1 Data

For the purposes of this study, the same data was applied to both market cleanliness methodologies. Announcement data from 2011 to 2016 and stock and index prices from 2010 to 2016 were utilized for the calculations.

All the methods used in this study can be calculated using publicly available data. However, private data was nonetheless used in order to avoid errors in collecting and adjusting public data.

The analysis performed in this study focused on announcements disclosed by companies whose stocks made up the Bovespa Index, abbreviated as Ibovespa. The choice over the Ibovespa's constituent stocks stems from the difficulty in detecting abnormal returns in illiquid shares and the relevance of those assets for the Brazilian capital market.

The Ibovespa is considered as the prime index for the Brazilian stock market. It provides a benchmark for the market's average performance, tracking the more actively traded stocks in the market. Although there was a change in methodology starting from 2014 in order to better and more accurately reflect the performance of the Brazilian stock market, the modification should not impact overall measuments of informed trading.

The index is compiled and announced by BM&FBovespa, the only stock exchange in Brazil, largest one in Latin America, located in São Paulo. According to BM&FBovespa (2014b), "the Ibovespa is composed exclusively of shares and units representing shares of BM&FBovespa listed issuers that meet the inclusion criteria." The inclusion criteria are mainly based on the number of trades and volume traded. It is a gross total return index weighted by market capitalization attributable to the free float per constituent.

The information about companies' announcements is public and can be obtained at the Securities and Exchange Commission of Brazil's (CVM) website, the Brazilian stock exchange BM&F Bovespa's website and several other news sources. However, the compiled announcement dataset could not be extracted

Table 1 – Ibovespa historic statistics

Date	Index Closing Rates	Number of Constituents	Index Market Value (Trilion BRL)	Total Market Value* (Trillion BRL)
2010	69,304.81	62	2.07	2.56
2011	56,754.08	63	1.83	2.29
2012	60,952.08	63	2.00	2.52
2013	51,507.16	66	1.89	2.41
2014	50,007.41	66	1.82	2.24
2015	43,349.96	60	1.59	1.91
2016	60,227.28	55	2.08	2.47

Source: www.bmfbovespa.com.br
* Information from "Notice to Market," market value of the all companies listed on BM&FBovespa

from theses sources, as the website interface only allows the visualization of individual information consultations. Manually compiling the data necessary for this analysis by copying the information one at a time would likely provoke errors. On that account, the historical company announcement data used in this analysis was obtained from the CVM's Office of Market Surveillance (SMI).

Only announcements classified as "fato relevante" (relevant event) were used for this analysis. Among the announcements, there are 44 different classifications on the BM&FBovespa website. Even though there might exist relevant information incorrectly classified or even material information that was not publicly disclosed, most price-sensitive information should be labeled as "fato relevante" and will serve the purpose of this event study.

To determine which announcements were generated by companies that made up the Ibovespa at the time they were disclosed, the Ibovespa historical composition was obtained after requesting it through BM&FBovespa's customer service. BM&F Bovespa did not have the historical composition of the Ibovespa available on its website for the entire period from 2011 to 2016.

The set of announcements used in this study was summarized in table 2. The number of announcements has remained fairly constant over the period analyzed. This analysis only includes the announcements classified as "fato relevante" that were issued by companies that were part of the Ibovespa at the time they were disclosed.

Table 2 – Announcements from the Ibovespa companies

Period	2011	2012	2013	2014	2015	2016	Total
Number of announcements *	417	376	404	470	373	433	2473
Distinct announcement days**	370	345	361	411	331	384	2202

* May contain more than one announcement from a company in the same day.
** Considers only one announcement per day per company.

Note that a company can issue more that one announcement in the same day. For this study, we will consider as an event for a specific security any trading day that possesses an announcement, regardless of how many annoucements there is in that day. Therefore, in table 2, the number of distinct announcement days only considers one announcement per day for each company.

It is also important to mention that a company is allowed to issue shares with different classes. According to the Ibovespa constituents selection criteria, it is possible to have more than one class of shares from the same company as part of the Ibovespa in the same period.

BM&FBovespa S.A. provides all historical daily prices for all the securities traded on its stock exchange. However, those prices are not adjusted for dividend distribution and stock splits. Even though splits and distribution information is also public, in order to avoid errors collecting and adjusting prices, daily adjusted prices used in this study were extracted from Bloomberg Professional service, also known as "Bloomberg Terminal," from Bloomberg L.P. Closing prices were adjusted to take into account dividends, splits, rights and spinoffs.

All ticker changes, companies' mergers, and acquisitions during the period analyzed were considered for the analysis. Delisted stocks and new stocks that did not cover the entire analysis period but had enough information for the estimation, pre-event, and event windows described in figure 2 were included.

This study was conducted using public information and RStudio, an open source integrated development environment (IDE) for a programming language for statistical computing named "R." This allows anybody to easily conduct the same analysis described in the paper. For a list of software and library versions of R packages used for the calculations see appendix D. The code used in the analysis can be found in appendix E.

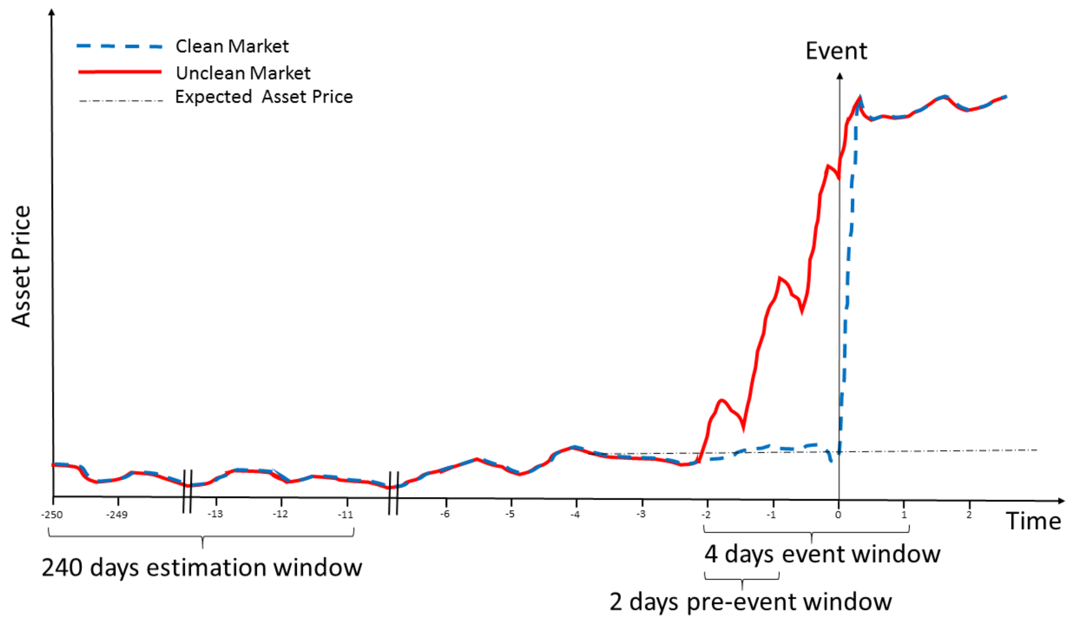


Figure 2 – Informed trading calculation windows

In order to compare results between methods, we utilized the same length of estimation, pre-event, and event windows for all informed trading calculations as those used in Dubow and Monteiro (2006) and Monteiro et al. (2007). The estimation window was set to 240 trading days long and ending 10 trading days before the announcement day. The pre-event window is set to two trading days long and immediately before the announcement day. The event window is four trading days long, starts two trading days before the announcement day and ends one day after (figure 2).

2.2 Analysis using Method A

This subsection attempts to replicate the methodology proposed by Dubow and Monteiro (2006) using Brazilian equities market data. The detailed mathematical specifications are described in subsection 2.2.1.

Each company's announcement is considered an event that might impact the firms' security prices. The calculations were repeated for all companies that made up the Ibovespa from 2011 to 2016. It is important to highlight that one company can issue more than one security, which means that each announcement will affect the prices of all securities issued by this firm.

In order to determine if an asset return presents an abnormal behavior, it is fundamental to establish what is considered normal behavior. The estimation window data was used to forecast the expected normal behavior for the asset which was later compared with the actual return from the event and pre-event window.

Arithmetic returns were used and the market model (12) was employed for the statistical model calculations over the estimation window. The market model describes the sensitivity of the expected asset return $E(R_{i,t})$ to the market portfolio $R_{m,t}$ for security i on trading day t.

$$E(R_{i,t}) = \alpha_i + \beta_i R_{m,t} \tag{12}$$

The market model can be used to evaluate a stock-specific sensitivity to non-diversifiable market risk. Using the Ibovespa as a proxy for the true market portfolio prevents us from classifying an abnormal return as statistically significant when stock price changes due solely to movements of the market as a whole.

A simple linear regression can be used to obtain the estimated model coefficients and the residual variance. After that, the daily abnormal returns for the estimation, pre-event, and event windows can be calculated. Abnormal return ($AR_{i,t}$) is obtained by subtracting the expected return estimated using the model coefficients from the actual asset return.

In order to evaluate the significance of the event, a four-day cumulative average return (${}^4CAR_i$) of the four trading days event window is calculated. This event window ${}^4CAR_i$ will be tested against the estimation window data for evaluating its significance. A statistical technique called bootstrap was used by taking 10,000 random samples of size four with replacement from the estimation window's $AR_{i,t}$ in order to create simulated data with better distribution properties than our initial sample.

The assumption that during the estimation window period the stock has a "normal behavior" implies that there is no significant news disclosed in that period. However, if this assumption is not valid, changes in price during this period could lead to invalid inferences. Hypothesis testing using quantiles can minimize the effects of outliers on the distribution, making the results more robust in case news are disclosed during the estimation window period.

If the event window ${}^4CAR_i$ is lower than the 50$^{\text{th}}$ most negative simulated four-day cumulative average return (${}^4CAR_i^*$) or greater than the 50$^{\text{th}}$ most positive ${}^4CAR_i^*$, the event will be classified as statistically significant at 1% level (two-tailed test), and the announcement is considered as a significant announcement (SA). Note the use of * in the notation to refer to the simulated samples from the bootstrap.

In a similar way, for evaluating the price movements during the pre-event window, when a significant event has occurred, a two-day ${}^2CAR_i$ of the two trading days pre-event window is calculated. After that, a second bootstrap of 10,000 samples of size two with replacement from the estimation window $AR_{i,t}$ is used to obtain ${}^2CAR_i^*$. If the pre-event window ${}^2CAR_i$ is lower than the 500$^{\text{th}}$ most negative ${}^2CAR_i^*$ or greater than the 500$^{\text{th}}$ most positive ${}^2CAR_i^*$, the pre-event price movement is significant at 10% level (two-tailed test). If a significant pre-event price movement occurs in the same direction of the event price movement, which means that the event window ${}^4CAR_i$ and the pre-event window ${}^2CAR_i$ are both positive or both negative, the event will be classified as having informed price movement (IPM) ahead of announcement.

Running this analysis through all the companies' announcements and theirs related securities, we can obtain the total number of IPMs and the total number of significant announcements (SA). The results can be biased upward due to the circularity approach of the methodology applied. Large two-day cumulative abnormal returns may contribute to four-day cumulative abnormal returns to be considered significant, which means significant announcements are more likely to have IPMs and therefore the proportion of IPMs may be overestimated.

Since the proportion of informed price movements (IPMs) calculated may present an upward bias, the approach labeled "method 1" by Dubow and Monteiro (2006) was used for adjusting the informed trading results.

Assuming that the asset behavior during the estimation window is not influenced by any significant news, if we calculate ${}^4CAR_i^*$ and ${}^2CAR_i^*$ from random samples extracted from the estimation window data, we should be able to estimate how many events would have been incorrectly classified as SA and IPM when there are no genuine new information affecting returns.

To estimate the bias correction, we performed the same calculations for the informed trading index but instead of comparing the ${}^{4}CAR_i^*$ 99.5% and 0.5% quantile with the actual event window ${}^{4}CAR_i$, we compared it with 10,000 ${}^{4}CAR_i^*$ from a third bootstrap sampled from the estimation window. The proportion of expected fake significant announcements (SA_{fake}) is given by the average of SAs associated with no new information.

Also, the ${}^{2}CAR_i^*$ 95.0% and 5.0% quantile should be compared with the 10,000 ${}^{2}CAR_i^*$ calculated from the first two elements of each sample from the third bootstrap. The average of IPMs identified by the methodology when no news has occurred determines the proportion of expected fake informed price movements (IPM_{fake}).

The adjusted number of significant announcements and the adjusted number of informed price movements are calculated by subtracting SA_{fake} from the SA and by subtracting IPM_{fake} from IPM, respectively. The informed trading index can be calculated by dividing the latter by the former as described in (13).

$$Informed\,trading\,index = \frac{\sum IPM - \sum IPM_{fake}}{\sum SA - \sum SA_{fake}} \tag{13}$$

2.2.1 Detailed description of Method A

Although it was not explicitly mentioned in Dubow and Monteiro (2006), to replicate this methodology we used arithmetic daily returns ($R_{i,t}$) of security i on trading day t calculated using adjusted prices ($P_{i,t}$), and simple index daily returns ($R_{m,t}$) on day t using the Ibovexpa index ($Ibov_t$) as a proxy for the market.

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{14}$$

$$R_{m,t} = \frac{Ibov_t - Ibov_{t-1}}{Ibov_{t-1}} \tag{15}$$

The methodology utilizes the market model and calculates a simple linear regression (16) for each announcement from a company, where $u_{i,t}$ are errors independent and identically distributed (iid). The announcement day will be considered $t = 0$ if the announcement takes place on a trading day, the following trading day will be considered $t = 0$ otherwise.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + u_{i,t}\ , \quad t = -250, \dots, -11 \tag{16}$$

The model's estimated coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ were used for calculating the expected asset returns (17) for the estimation window ($t = -250, ..., -11$), the pre-event window ($t = -2, -1$), and event window ($t = -2, ..., 1$). Abnormal return ($AR_{i,t}$) is calculated as a difference of the actual asset return and the expected asset return.

$$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t}\ , \quad t = -250, \dots, -11, -2, ..., 1 \tag{17}$$

$$AR_{i,t} = R_{i,t} - E(R_{i,t})\ , \quad t = -250, \dots, -11, -2, ..., 1 \tag{18}$$

A bootstrap technique and quantile thresholds were used to assess if the change in asset prices during the event window and the pre-event window were considered significant.

In order to examine if there was a significant change in price during the four-day event window, first we extracted 10,000 random samples of size four from the abnormal returns in the estimation window ($AR_{i,t}\ ,\ t = -250, \dots, -11$) with replacement and computed a simulated four-day cumulative abnormal return for each sample, resulting in 10,000 ${}^4CAR_i^*$ values. Note the use of * in the notation to refer to the simulated samples from the bootstrap.

As we used arithmetic returns, the aggregated abnormal return should not be calculated as simple sum using cumulative abnormal return (CAR). However, Brooks (2014) points out that "over short windows. discrepancies between models are usually small and any errors in the model specification are almost negligible." Therefore, we maintained the calculation of CAR as a simple sum.

After that, we determined the 99.5% quantile and the 0.5% quantile from the 10,000 ${}^4CAR_i^*$ (19) to be the upper and lower limit respectively for the assessment of the event window, i.e specifying the 1% most extreme values.

If the actual four-day cumulative abnormal return from the event window (${}^4CAR_i = \sum_{t=-2}^{1} AR_{i,t}$) is larger that the 99.5% quantile or lower than the 0.5%

quantile, the announcement is considered statistically significant at the 1% level for the security i and is classified as significant announcement (SA).

$$^{4}CAR_i^* = \sum_{j=1}^{4} AR_{i,j}^* \tag{19}$$

$$^{2}CAR_i^* = \sum_{j=1}^{2} AR_{i,j}^* \tag{20}$$

A similar process is performed to determine if the price change during the two-day pre-event window is considered significant. Using the bootstrap technique, 10,000 random samples of size two from the abnormal returns in the estimation window ($AR_{i,t}$, $t = -250, \ldots, -11$) with replacement were used to calculate simulated two-day cumulative abnormal returns $^{2}CAR_i^*$ (20) for each sample.

The actual two-day cumulative abnormal return from the pre-event window ($^{2}CAR_i = \sum_{t=-2}^{-1} AR_{i,t}$) is considered statistically significant at the 10% level if it is larger that the 95% quantile or lower than the 0.5% quantile from the 10,000 $^{2}CAR_i^*$ distribution.

The announcement is classified as having an informed price movement (IPM) if the four-day event window is considered significant, the two-day pre-event window is also considered significant, and $^{4}CAR_i$ and $^{2}CAR_i$ are in the same direction, i.e. both have positive or negative values.

This procedure is repeated for all securities i of all companies j included in the study, for $i = 1, ..., N$, where N is the number of securities issued by company j, and $j = 1, ..., M$, where M is the number of companies that were part of the Ibovespa. The informed trading index is calculated by dividing the sum of all IPMs by the sum of all significant announcements.

$$Informed\,trading\,index_{unadjusted} = \frac{\sum_{j}^{M}\sum_{i}^{N} informed\,price\,movement\,(IPM)}{\sum_{j}^{M}\sum_{i}^{N} significant\,announcement\,(SA)} \tag{21}$$

2.2.2 Bias Correction

For each announcement from a company, the linear regression from (22) was estimated.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + u_{i,t} \ , \quad t = -250, \ldots, -11 \tag{22}$$

The model's estimated coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ were used for calculating the expected asset returns, which was then used to determine the abnormal returns ($AR_{i,t}$) from for the estimation window ($t = -250, ..., -11$).

$$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} \ , \quad t = -250, \ldots, -11 \tag{23}$$

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \ , \quad t = -250, \ldots, -11 \tag{24}$$

The bootstrap technique was used to create 10,000 random samples of size four from the abnormal returns in the estimation window ($AR_{i,t} \ , \ t = -250, \ldots, -11$) with replacement and compute simulated four-day cumulative abnormal return (${}^4CAR_i^*$) for each sample, resulting in 10,000 values. These simulated CARs were used to determine the quantile thresholds ${}^4Upper = 99.5\% \, quantile$ and ${}^4Lower = 0.5\% \, quantile$.

More 10,000 random samples of size two from the abnormal returns in the estimation window with replacement were obtained from a second bootstrap. After calculating 10,000 two-day cumulative abnormal return (${}^2CAR_i^*$), the quantile thresholds ${}^2Upper = 95\% \, quantile$ and ${}^2Lower = 5\% \, quantile$ were computed.

A third bootstrap produced 10,000 random samples of size four from the abnormal returns in the estimation window with replacement. For each of these four-day samples, a two-day cumulative abnormal return (${}^2CAR_i^*$) and a four-day cumulative abnormal return (${}^4CAR_i^*$) were calculated using the first two days of the sample and all four days, respectively. This simulation produces 10,000 fake four-day event window returns and 10,000 fake two-day pre-event window returns that will be used to estimate the proportion of significant price movements that are associated with significant announcements when no news was expected to have occurred.

$$^4CAR_i^* = \sum_{j=1}^{4} AR_{i,j}^* \tag{25}$$

$$^2CAR_i^* = \sum_{j=1}^{2} AR_{i,j}^* \tag{26}$$

In each sample from the third bootstrap, each sample simulates and announcement. If the $^4CAR_i^*$ is larger than ^4Upper or lower than ^4Lower, we can classify this simulated announcement as significant. Also if the $^2CAR_i^*$ is in the same direction as $^4CAR_i^*$ (both negative or both positive) and if $^2CAR_i^*$ is larger than ^2Upper or lower than ^2Lower; the simulated announcement would be considered as having an informed price movement.

The average of significant simulated announcements and the average of simulated announcements which would be considered as having an informed price movement equal SA_{fake} and IPM_{fake}, respectively.

$$SA_{fake} = \frac{\sum significant\, simulated\, announcement}{10,000} \tag{27}$$

$$IPM_{fake} = \frac{\sum simulated\, informed\, price\, movement}{10,000} \tag{28}$$

Repeating the procedure for all companies' announcements and theirs related securities, we can estimate the expected number of false significant announcements as the sum of all SA_{fake} and the expected number of false IPMs associated with those significant announcements as the sum of all IPM_{fake}.

Therefore, the adjusted measure of informed trading if given by the (29), for $i = 1, ..., N$, where N is the number of securities issued by company j, and $j = 1, ..., M$, where M is the number of companies included in this study.

$$Market\, cleanliness\, index = \frac{\sum_{j}^{M}\sum_{i}^{N} IPM - \sum_{j}^{M}\sum_{i}^{N} IPM_{fake}}{\sum_{j}^{M}\sum_{i}^{N} SA - \sum_{j}^{M}\sum_{i}^{N} SA_{fake}} \tag{29}$$

2.2.3 Results of Method A

Table 3 summarizes the results using the methodology described in the previous subsections applied to all announcements classified as "fato relevante" (relevant event) from 2011 to 2016 by companies that were part of the Ibovespa at the time of the announcement.

If two or more announcements were issued on the same day by the same company, these announcements were treated as a single announcement for the purpose of this study. In addition, if multiple classes of stock issued by a company were part of the Ibovespa, the impact of each announcement by the company on prices of all classes of stock was assessed.

In total, 2,671 events were analyzed but only 2,608 produced valid results. One company didn't have any announcements classified as "fato relevante" during the period while it was part of the Ibovespa. Mostly due to delisted stocks and changes in stock ticker, 63 events didn't have enough data for the methodology estimation.

Table 3 – Informed trading measure using the Method A

Period	Announcements	SA	IPM	SA_{fake}	IPM_{fake}	Unadjusted Measure	Informed Trading
2011	443	18	10	4.49	3.05	55.6%	51.4%
2012	398	24	14	4.08	2.75	58.3%	56.5%
2013	416	26	21	4.25	2.89	80.8%	83.3%
2014	468	26	22	4.83	3.25	84.6%	88.5%
2015	393	23	18	3.99	2.71	78.3%	80.4%
2016	490	17	10	4.96	3.39	58.8%	54.9%
2011-2016	2608	134	95	26.58	18.04	70.9%	71.7%

This analysis attempted to reproduce the methodology from Dubow and Monteiro (2006) that used the United Kingdom's (UK) data. UK's measurements showed an average market cleanliness of 31.3% (1998 to 2000) and 32.1% (2002 and 2003) using FTSE 350 index securities. It is important to point out that even though the calculation methodology was similar, the period examined was different and Dubow and Monteiro (2006) selected only announcements headed "trading statement," "trading update," "contract award" or "drilling report" while this study was more comprehensive using all announcements classified as "fato relevante" (relevant event).

A similar methodology was also employed by ASIC (2016) using Australian data. The Australian results for market cleanliness were below 20%, from 2006 to October 2015 . A summary of the UK and Australian measurements is displayed in appendix B.

Some preliminary observations about the results from table 3 can be made. First of all, compared to the UK's and Australian results, the level of informed trading is high, 71.7% on average from 2011 to 2016.

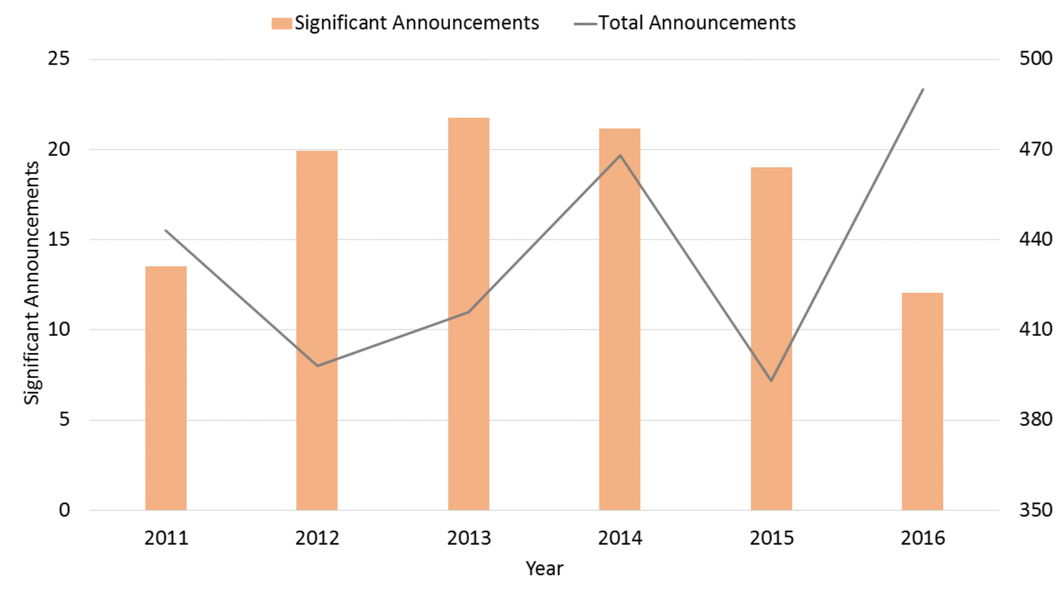
In addition, the results from years 2013 to 2015 showed perceptible higher values. During the same period, the bias correction increased informed trading values, even though the adjustment for circularity effect was expected to reduce them.

The bias correction results were within expectations. Due to the level of confidence chosen, we would expect 1% of all announcements to be incorrectly classified as significance announcements (SA) and results from Dubow and Monteiro (2006) indicate that over two-thirds of SAs are incorrectly classified as informed price movements (IPM) with the bias correction method employed. On table 3, we can observe that SA_{fake} correspond to 1.02% of all announcements and 67.87% of SA_{fake} were classified as IPM_{fake}.

A comparison between the number of significant announcements (SA) detected and total announcements analyzed was made in order to verify if the increase in SAs during the period of 2012 to 2015 could have occurred due to an increase in the number events evaluated in this period.

Figure 3 shows that number of SA classified by this method is not correlated to the total number of announcements evaluated per year. Therefore, a larger number of events evaluated does not necessarily result in a larger measurement of significant announcements.

Similarly, figure 4 illustrate that the informed trading measurement is also not correlated to the total number of announcements.



* Significant announcement measure adjusted by bias correction

Figure 3 – Comparison of significant announcements and total announcements

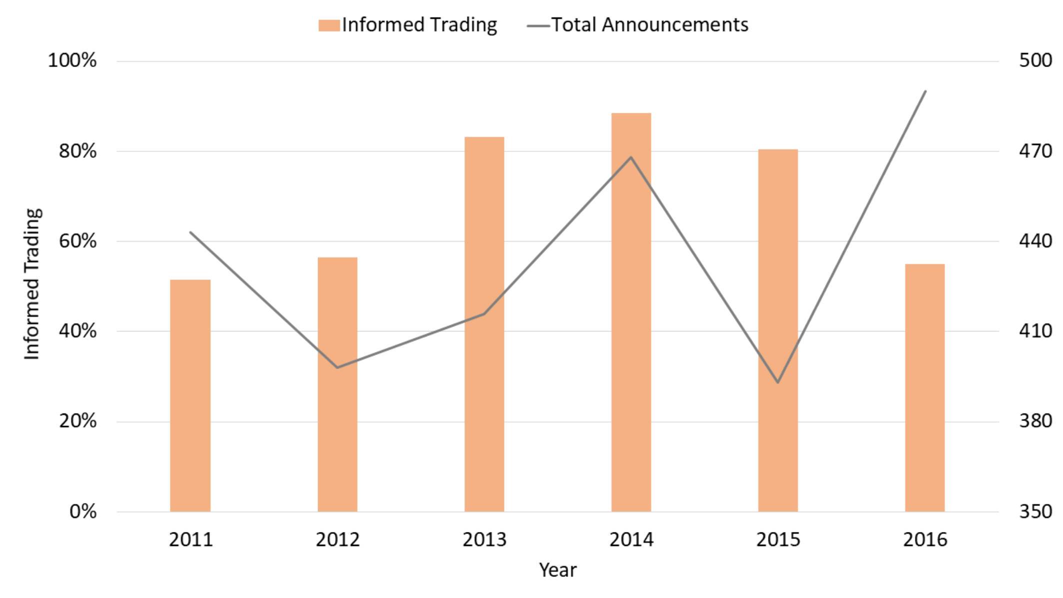


Figure 4 – Comparison of informed trading and total announcements

2.3 Analysis using Method B

This subsection attempts to replicate the market cleanliness methodology proposed by Monteiro et al. (2007) using Brazilian equities market data. The detailed mathematical specifications are described in subsection 2.3.1.

This methodology presents improvements over the one proposed by Dubow and Monteiro (2006) since it takes into consideration the possibility of serial correlation and heteroskedasticity for the model estimation and devises an unbiased identification method for the hypothesis testing.

Each company's announcement is considered an event that might impact the company's securities prices and the calculations were repeated for all companies that were part of the Ibovespa from 2011 to 2016.

In order to determine if an asset return presents an abnormal behavior, it is fundamental to establish what is considered normal behavior. The estimation window data was used to forecast the expected normal behavior for the asset which was later compared with the actual returns from the event and pre-event windows.

Using the Ibovespa returns ($R_{m,t}$) as an explanatory variable prevents us from classifying an abnormal return as statistically significant when stock price changes due solely to movements of the market as a whole. The most simple model for estimating the asset daily returns ($R_{i,t}$) would be a simple linear regression (30). However, that might not satisfy the homoscedasticity and no serial correlation of errors assumptions for OLS estimators.

To improve the forecast values derived from the statistical model and make more reliable inferences, tests were conducted to determine if the assumptions hold. The Durbin's alternative test was utilized to verify the presence of serial correlation and the Engle's LM test was performed in order to evaluate the presence of heteroskedasticity. Based on the results obtained from the tests, different models were applied to estimate the parameters over the estimation window.

Provided that the tests reveal no presence of serial correlation and heteroskedasticity, which means that the OLS assumptions hold, a linear regression model (LR) described in (30) was used to estimate the parameters over the estimation window.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + u_{i,t} \tag{30}$$

If the tests detected the presence of serial correlation but no heteroskedasticity, an autoregressive distributed lag model (ADL) (31) was used instead. In this model, the independent variables include dependent and independent variables of the market model in an once lagged form, i.e. ADL(1,1). It is a more complex and dynamic model than the Cochrane-Orcutt method which is often used for serial correlation correction.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \gamma_i R_{i,t-1} + \delta_i R_{m,t-1} + \epsilon_{i,t} \tag{31}$$

In case there was heteroskedasticity but not serial correlation, the returns would still be modeled using the linear regression model (32) but considering that the error variance follows a generalized autoregressive conditional heteroskedasticity model (LR-GARCH) (33).

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + u_{i,t} \tag{32}$$

$$\sigma_t^2 = \omega + a\, \hat{u}_{i,t-1}^2 + b\sigma_{t-1}^2 + \epsilon_{i,t} \tag{33}$$

The GARCH model is commonly applied to analysis using financial time series to describe volatility clustering, where periods of relatively low volatility and periods of high volatility show some persistence.

According to Engle (2001), "in the presence of heteroskedasticity, the regression coefficients for an ordinary least squares regression are still unbiased, but the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of precision." GARCH model treats heteroskedasticity as a variance to be modeled according to (33), where $\hat{u}_{i,t}^2$ is the square of residuals from the linear regression, σ_{t-1}^2 is the square of the first lag of the residual conditional variance and $\epsilon_{i,t}$ is the error term.

An autoregressive distributed lag model with the error variance following a generalized autoregressive conditional heteroskedasticity model (ADL-GARCH (34) and (35)) is utilized in case the tests indicate the presence of both serial correlation and heteroskedasticity.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \gamma_i R_{i,t-1} + \delta_i R_{m,t-1} + u_{i,t} \tag{34}$$

$$\sigma_t^2 = \omega + a\,\hat{u}_{i,t-1}^2 + b\sigma_{t-1}^2 + \epsilon_{i,t} \tag{35}$$

After determining which statistical model will be applied, the daily abnormal returns for the estimation, pre-event and event windows can be calculated.

Standardized abnormal returns ($SAR_{i,t}$) are obtained by subtracting the expected return estimated using the model coefficients from the actual asset return and dividing the result by the square root of the residual variance.

Bootstrapping allows estimation of the sampling distribution using random sampling methods with replacement. However, to avoid the circularity approach bias described by Dubow and Monteiro (2006), a technique called "conditional bootstrap" was used to evaluate the significance of the event and the pre-event cumulative average returns (CARs). By evaluating the pre-event CAR conditional on the event CAR being significant, we are able to eliminate the bias.

The four-day cumulative average return (${}^4CAR_i$) of the event window is calculated. This event ${}^4CAR_i$ will be compared to the estimation window data for establishing its significance.

The first bootstrap was performed by taking 50,000 samples of size four with replacement from the estimation window $SAR_{i,t}$ and calculating ${}^4CAR_i^*$ for each sample. Note the use of * in the notation to refer to the simulated samples from the bootstrap.

If the event window ${}^4CAR_i$ is lower than the 250$^{\text{th}}$ most negative (99.5% quantile) simulated four-day cumulative average return (${}^4CAR_i^*$) or greater than the 250$^{\text{th}}$ most positive (0.5% quantile) ${}^4CAR_i^*$, the event is statistically significant at 1% level (two-tailed test). Therefore, the event will be classified as a significant announcement (SA).

When a significant event has occurred, a two-day ${}^2CAR_i$ of the pre-event window is calculated for evaluating the price movements during this period.

After that, a second bootstrap of 50,000 samples of size four with replacement from the estimation window $SAR_{i,t}$ is used to obtain ${}^4CAR_i^*$ for each sample. For the evaluation will only be considered the samples whose ${}^4CAR_i^*$ are larger than the 99.5% quantile or smaller than the 0.5% quantile from the first bootstrap. On the filtered samples, a ${}^{2}CAR_i^*$ is calculated using the first two days of each sample.

If the event ${}^{4}CAR_i$ is positive, an informed price movement (IPM) will have occurred when the pre-event window ${}^{2}CAR_i$ is higher than the 50$^{\text{th}}$ most positive ${}^{2}CAR_i^*$ from the second bootstrap.

On the other hand, if the event ${}^{4}CAR_i$ is negative, the event will be classified as having an IPM when the pre-event window ${}^{2}CAR_i$ is lower than the 50$^{\text{th}}$ most negative ${}^{2}CAR_i^*$, a level of significance of 10% one-tailed.

If the assumption that no significant news were disclosed during the estimation window period is not correct, the changes in price during this period could lead to invalid inferences. Using bootstrap and quantiles to test the event and pre-event returns significance is a robust technique since it is less affected by outliers.

Running this analysis through all the companies' announcements and theirs related securities, we can obtain the informed trading index by dividing the total number of IPMs and the total number of significant announcements (SA) as described in the (36).

$$Informed\, trading\, index = \frac{\sum IPM}{\sum SA} \tag{36}$$

2.3.1 Detailed description of Method B

In order to replicate this methodology described in Monteiro et al. (2007), we used simple or arithmetic daily returns ($R_{i,t}$) of security i on trading day t calculated using daily adjusted prices ($P_{i,t}$), and arithmetic index daily returns ($R_{m,t}$) using the Ibovexpa index ($Ibov_t$) as a proxy for the market.

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{37}$$

$$R_{m,t} = \frac{Ibov_t - Ibov_{t-1}}{Ibov_{t-1}} \tag{38}$$

For each announcement from a company, the time series simple linear regression described in (39) is estimated for $i = 1, ..., N$, where N is the number of securities issued by the company and $u_{i,t}$ are errors.

The announcement day will be considered $t = 0$ if it takes place during a trading day, or the next trading day will be considered $t = 0$ otherwise.

Using the market as an explanatory variable allows us to disregard price changes that were caused by movements of the market as a whole.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + u_{i,t}\ , \quad t = -250, \ldots, -11 \tag{39}$$

The model (39) assumes that the residuals $\hat{u}_{i,t}$ are independent and identically distributed (iid). However, these assumptions might not hold for the data being analyzed. If the residuals are serially correlated or the variance or the returns changes over time (heteroskedasticity), the residuals won't be iid and the model to describe the behavior of the security return could be improved.

In order to test the presence of serial correlation, a Durbin's alternative test was utilized. Durbin's alternative test is, in fact, an LM test. It is more easily computed with a Wald test on the coefficients of the lagged residuals in an auxiliary OLS regression. The auxiliary regression of the residuals on their lags and all the covariates of the original regression is described by (40), where $R_{m,t}$ is the explanatory variable from the original linear regression from (39) and the term $\epsilon_{i,t}$ stands for the random-error term.

$$\hat{u}_{i,t} = \rho_0 \hat{u}_{i,t-1} + \rho_1 R_{m,t} + \epsilon_{i,t} \tag{40}$$

$$H_0 : \rho_0 = 0 \tag{41}$$

$$H_1 : \rho_0 \neq 0 \tag{42}$$

Durbin's alternative test is then obtained by performing a Wald test where all coefficients from the residuals lags are jointly zero. The null hypothesis (41) of no first-order serial correlation versus the alternative (42) that residuals follow an AR(1) process was tested for a significance level of 5%. The test was made robust to an unknown form of heteroskedasticity by using a robust heteroskedasticity-consistent covariance matrix estimator for the auxiliary regression (39).

If the test fails to reject the null hypothesis, this suggests that removing lagged residual will not substantially harm the fit of that model, but if the p-value is less than 0.05, the null hypothesis is rejected indicating that there is serial correlation.

After that, the Engle's LM test was performed in order the evaluate the presence of heteroskedasticity in the time series. A time series exhibiting conditional heteroskedasticity (autocorrelation of the squared residuals) is said to have autoregressive conditional heteroskedastic (ARCH) effects. Therefore, the Engle's LM test was used to evaluate ARCH(1) effects using the Lagrange multiplier test.

The auxiliary regression of the squared residuals on their first order lags is described by (43). The null hypothesis (44) of absence of ARCH(1) effect versus the alternative hypothesis (45) of presence of significant coefficient for the ARCH(1) component was tested for a significance level of 5%. If the p-value is less than 0.05, the null hypothesis is rejected, indicating presence of heteroskedasticity in the time series.

$$\hat{u}_{i,t}^2 = \varphi_0 + \varphi_1 \hat{u}_{i,t-1}^2 + \epsilon_{i,t} \tag{43}$$

$$H_0 : \varphi_1 = 0 \tag{44}$$

$$H_1 : \varphi_1 \neq 0 \tag{45}$$

Depending on the results of the Durbin's alternative test for serial correlation and the Engle's LM test for heteroskedasticity, four different models were used to estimate the expected asset returns and the abnormal returns associated with them.

If neither serial correlation or heteroskedasticity were detected, it indicates that the residuals from the linear regression model (39) are in fact iid. The model's estimated coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ were used for calculating the expected asset returns (46).

Abnormal returns ($AR_{i,t}$) are determined as a difference of the expected asset return and the actual asset return and are computed from for the estimation window ($t = -250, ..., -11$), the pre-event window ($t = -2, -1$), and event window ($t = -2, 1$). Standardized abnormal (48) returns are simply $AR_{i,t}$ divided by the square root of their respective variance.

$$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t}\,, \quad t = -250, \ldots, -11, -2, ..., 1 \tag{46}$$

$$AR_{i,t} = R_{i,t} - E(R_{i,t})\,, \quad t = -250, \ldots, -11, -2, ..., 1 \tag{47}$$

$$SAR_{i,t} = \frac{R_{i,t} - E(R_{i,t})}{\sqrt{E(\sigma_t^2)}}\,, \quad t = -250, \ldots, -11, -2, ..., 1 \tag{48}$$

In case that only of serial correlation is identified, an autoregressive distributed lag model ADL(1,1) described in (49) is used to control for this effect. The model's estimated coefficients $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{\gamma}_i$ and $\hat{\delta}_i$ were used for calculating the expected asset returns. The standardized abnormal returns are calculated the same way as the previous case, using (47) and (48).

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \gamma_i R_{i,t-1} + \delta_i R_{m,t-1} + \epsilon_{i,t}\,, \quad t = -250, \ldots, -11 \tag{49}$$

$$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} + \hat{\gamma}_i R_{i,t-1} + \hat{\delta}_i R_{m,t-1}\,, \quad t = -250, \ldots, -10, -2, ..., 1 \tag{50}$$

Provided that there is only presence of heteroskedasticity demonstrated by the Engle's LM test but no indication of serial correlation, the returns would still be modeled using the linear regression model (39) but considering that the error variance follows a generalized autoregressive conditional heteroskedasticity GARCH model (51) and (52).

The expected returns are calculated with (46). As the variance changes over time, in order to be able to compare returns with different variances, the abnormal return should be standardized according to (48). It is not clear why Monteiro et al. (2007) calculated the estimated variance using different equations for the estimation window (53) and the rest of the time series (54), but the methodology was replicated nonetheless.

$$u_{i,t} = \sigma_t \epsilon_{i,t}\,, \quad t = -250, \ldots, -11 \tag{51}$$

$$\sigma_t^2 = \omega + a\,\hat{u}_{i,t-1}^2 + b\sigma_{t-1}^2 + \epsilon_{i,t}\,, \quad t = -250, \dots, -11 \tag{52}$$

$$E(\sigma_t^2) = \hat{\omega} + \hat{a}\,\hat{u}_{i,t-1}^2 + \hat{b}\sigma_{t-1}^2\,, \quad t = -250, \dots, -11 \tag{53}$$

$$E(\sigma_t^2) = \hat{\omega} + \hat{b}\sigma_{t-1}^2\,, \quad t = -9, \dots, 1 \tag{54}$$

If the test indicated the presence of both serial correlation and heteroskedasticity, an ADL(1,1) model would be used for calculating the expected returns (49) and (50) and a GARCH(1,1) would model the variance (51), (52), (53) and (54). The abnormal returns would be normalized according to (48).

Considering the results from the Durbin's alternative test and the Engle's LM test, one of the four models described previously was used to determine the asset's standardized abnormal returns $SAR_{i,t}$ (48).

For the bootstrap analysis, first we extracted 50,000 random samples with replacement of four standardized abnormal returns from the estimation window ($SAR_{i,t}\,,\ t = -250, \dots, -11$) and computed a simulated four-day cumulative abnormal return (${}^4CAR_i^*$) for each sample, resulting in 50,000 values. Note the use of * in the notation to refer to the simulated samples from the bootstrap.

As we used arithmetic returns, the aggregated abnormal return should not be calculated as simple sum using cumulative abnormal return (CAR). However, as Brooks (2014) points out, "over short windows. discrepancies between models are usually small and any errors in the model specification are almost negligible." Therefore, the calculation using CAR was maintained.

After that, we determined the 99.5% quantile (${}^4Upper = 99.5\%\,quantile$) and the 0.5% quantile (${}^4Lower = 0.5\%\,quantile$) from the 50,000 ${}^4CAR_i^*$ (55) as threshold limits for the assessment of the behavior over the event window, delimiting the 1% most extremes values.

If the actual four-day cumulative abnormal return from the event window (${}^4CAR_i = \sum_{t=-2}^{1} SAR_{i,t}$) is larger that the 99.5% quantile or lower than the 0.5% quantile, the announcement is considered statistically significant at the 1% level.

$$^{4}CAR_i^* = \sum_{j=1}^{4} SAR_{i,j}^* \tag{55}$$

$$^{2}CAR_i^* = \sum_{j=1}^{2} SAR_{i,j}^* \tag{56}$$

Conditional bootstrap was used to determined if the price change during the two-day pre-event window is considered significant. A second bootstrap produced 50,000 random samples of four standardized abnormal returns from the estimation window ($SAR_{i,t}$, $t = -250, \ldots, -11$) with replacement. For each sample, a simulated four-day cumulative abnormal return $^{4}CAR_i^*$ (55) and a two-day cumulative abnormal returns $^{2}CAR_i^*$ (56) were calculated using all four days and the first two days, respectively.

A subset of samples from the second bootstrap containing only $^{4}CAR_i^*$ that were larger than $^{4}Upper$ or lower than $^{4}Lower$ was selected.

If the actual four-day cumulative abnormal return from the event window ($^{4}CAR_i$) had a positive value, the two-day cumulative abnormal return from the pre-event window ($^{2}CAR_i = \sum_{t=-2}^{-1} SAR_{i,t}$) would be considered statistically significant at the 10% level if it was larger that the 90% quantile from the subset of samples from the second bootstrap.

On the other hand, if $^{4}CAR_i$ had a negative value, $^{2}CAR_i$ would be considered statistically significant at the 10% level if it was lower that the 10% quantile from the subset.

Significant $^{2}CAR_i$ were classified as exhibiting an informed price movement (IPM) before the announcement.

This procedure is repeated for all securities i of all companies j included in the study, for $i = 1, ..., N$, where N is the number of securities issued by a company j, and $j = 1, ..., M$, where M is the number of companies included in the Ibovespa. The informed trading index is calculated by dividing the sum of all IPMs by the sum of all significant announcements.

$$Informed\,trading\,index = \frac{\sum_{j}^{M}\sum_{i}^{N} informed\,price\,movement\,(IPM)}{\sum_{j}^{M}\sum_{i}^{N} significant\,announcement\,(SA)} \tag{57}$$

.

2.3.2 Results of Method B

Table 4 summarizes the results using the Method B applied to all announcements classified as "fato relevante" (relevant event) from 2011 to 2016 by companies were part of the Ibovespa at the time of the announcement.

If two or more announcements were issued on the same day by the same company, these announcements were treated as a single announcement for the purpose of this study. In addition, if multiple classes of stock issued by a company were part of the Ibovespa, the impact of each announcement by the company on prices of all classes of stock was assessed.

In total, 2,671 events were analyzed, 2,608 produced valid results, one company didn't have any announcements classified as "fato relevante" during the period while it was part of the Ibovespa and 63 events didn't have enough data for the methodology estimation, mostly due to delisted stocks and changes in stock ticker.

This analysis attempted to reproduce the methodology from Monteiro et al. (2007) that used the United Kingdom's data. Preliminary observations about the results from table 4 show that the level of informed trading is high, 58.2% on average from 2011 to 2016, compared to the UK's results.

UK's measurements exhibited an average market cleanliness of 19.6% (1998 to 2000), 11.1% (2002 and 2003) and 2.0% (2004 and 2005) using FTSE 350 index securities. It is important to point out that even though the calculation methodology was similar, the period examined was different and Monteiro et al. (2007) selected only announcements headed "trading update," "contract award" or "drilling report" while this study was more comprehensive using all announcements classified as "fato relevante" (relevant event). A summary of the results using UK data was published by Monteiro et al. (2007) and is summarized in appendix C.

Table 4 – Informed trading measure using the Method B

Period	Announcements	SA	IPM	Informed Trading
2011	443	20	10	50.0%
2012	398	30	14	46.7%
2013	416	39	24	61.5%
2014	468	27	17	63.0%
2015	393	23	17	73.9%
2016	490	19	10	52.6%
2011-2016	2608	158	92	58.2%

	No change	Serial correlation correction only	Heteroskedasticity correction only	SC correction* HK correction**	Total events
No serial correlation No heteroskedaticity	1574				1574
Serial correlation No heteroskedaticity	0	269			269
No serial correlation Heteroskedaticity	184		490		674
Serial correlation Heteroskedaticity	0	8	0	83	91
Total events	1758	277	490	83	2608

* SC stands for serial correlation
** HK stands for heteroskedasticity

Figure 5 – Serial correlation and heteroskedasticity correction after model selection

After correcting for serial correlation using the model described in (49), another Durbin's alternative test was performed on the residuals $\hat{\epsilon}_{i,t}$ to verify if the serial correlation was successfully removed. Also, for the cases that presented heteroskedasticity and were adjusted using (52), another Engle's LM test was conducted on squared residuals $\hat{u}^2_{i,t}$. The results were summarized in figure 5.

From 2608 valid announcements analyzed, the initial Durbin's alternative test performed suggested that 13.8% of them exhibited serial correlation, and the initial Engle's LM test concluded that 29.3% of them showed signs of heteroskedasticity. After the model correction, the same tests indicated that 0.0% exhibited serial correlation and only 7.4% of all valid announcements still indicated presence of heteroskedasticity. Therefore, after the model correction, 92.6% of all events evaluated satisfied the homoscedasticity and no serial correlation of errors assumptions for OLS estimators.

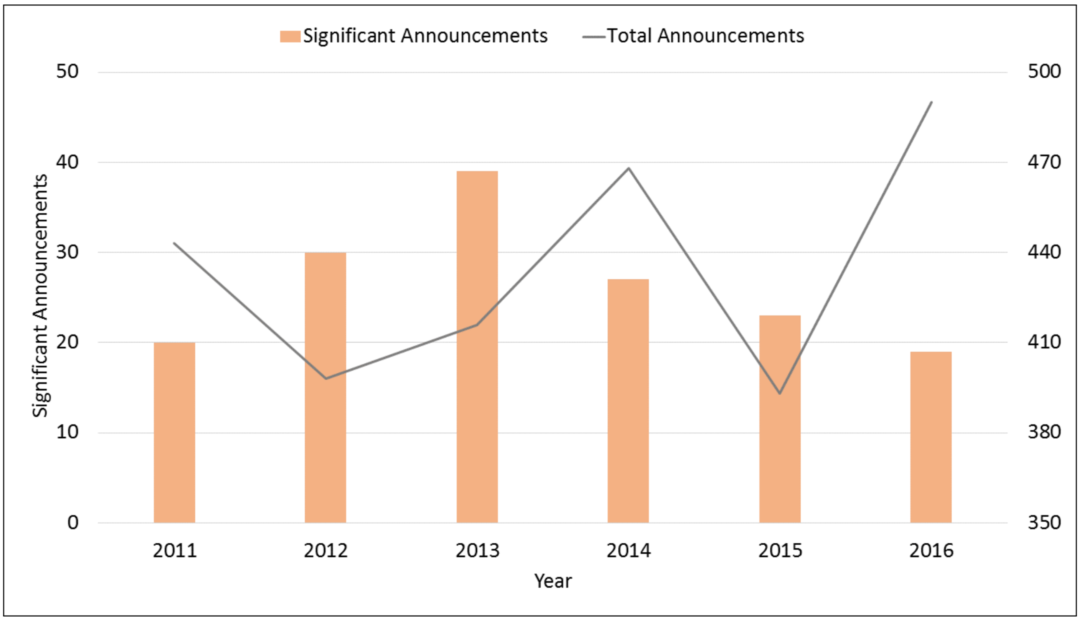


Figure 6 – Comparison of significant announcements and total announcements

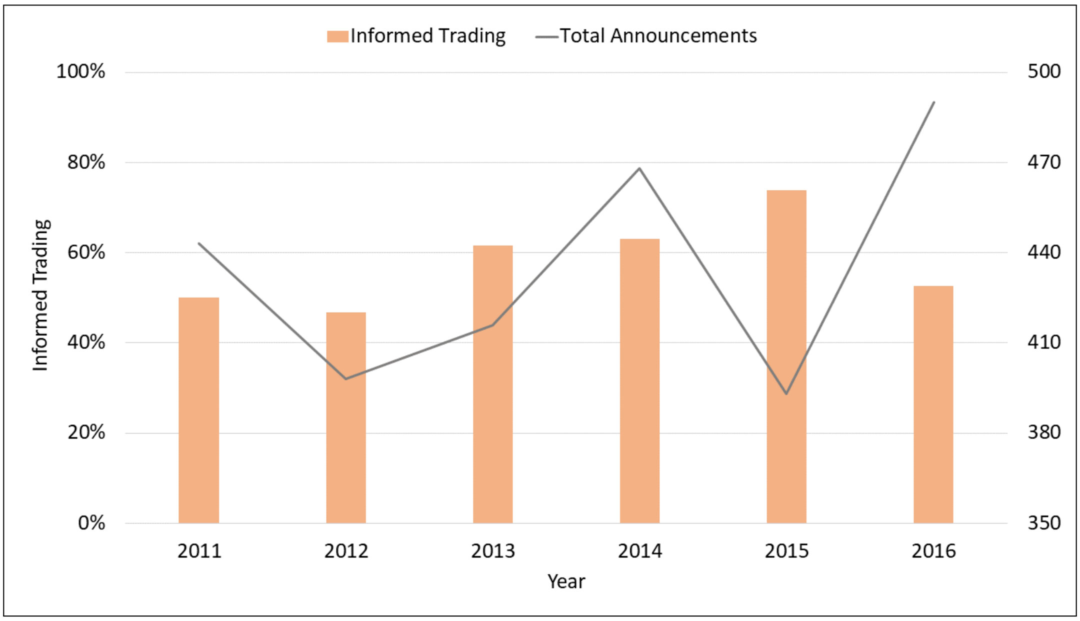


Figure 7 – Comparison of informed trading and total announcements

A comparison between the number of significant announcements (SA) detected and total announcements analyzed was made in order to verify if the increase in SAs during the period of 2012 to 2015 could have occurred due to an increase in the number events evaluated in this period.

Figure 6 shows that number of SA identified by this method is not correlated to the total number of announcements evaluated per year. Similarly, figure 7 illustrate that the informed trading measurement is also not correlated to the total number of announcements.

2.4 Interpretation of Results

The same data was analyzed using 2 different methods for estimating informed trading. Even though many aspects of the methodology were different, both method consistently indicated that informed trading index using Brazilian equity data provided high values when compared with the United Kingdom's (UK) and Australia's measurements. Brazilian results are summarized in table 5 while UK's and Australian market cleanliness values are displayed in appendixes B and C.

The analysis performed by Dubow and Monteiro (2006), Monteiro et al. (2007) and the Australian results by ASIC (2016) obtained lower values for market cleanliness. The difference in size of the equity market and its liquidity make it difficult to directly compare results. In the UK's case, the period and event selection choices were distinct, but in the Australian case, the time period and the event selection criteria are similar to this study.

Informed trading results from years 2013 to 2015 were above average for both methods. However, Method B seems to better account for the circularity problem than Method A's bias correction. All measurements under Method B are lower than Method A's unadjusted measure as expected, since the circularity effect tends to overestimates informed price movements (IMP) detection.

According to figure 5, Method B is able to better model the asset behavior in 32.6% of the cases, thus inferences results are more accurate. Of all estimation window time series regressed under Method A, 39.7% presented either serial correlation, heteroskedasticity or both. For the second model, the number drops to 7.4%.

Table 5 – Comparison of Method A and Method B

Period	Method A		Period	Method B
	Unadjusted Measure	Informed Trading		Informed Trading
2011	55.6%	51.4%	2011	50.00%
2012	58.3%	56.5%	2012	46.7%
2013	80.8%	83.3%	2013	61.5%
2014	84.6%	88.5%	2014	63.0%
2015	78.3%	80.4%	2015	73.9%
2016	58.8%	54.9%	2016	52.2%

An empirical study conducted by Bhattacharya and Daouk (2002) concluded that "it is the enforcement, not the existence of insider trading laws, that matters." The study suggests that the existence of insider trading laws alone is not sufficient to improve market efficiency. Evidences provided by Monteiro et al. (2007) indicate that Method B was able to indicate a small decline in the informed trading measure after the introduction of the Financial Services and Markets Act (FSMA) and a sharp drop after the first insider trading enforcement case was brought by the FSA under the new regulation.

There have not been any significant changes in Brazilian securities regulation regarding insider trading or listed companies disclosure requirements during the period analyzed. Nonetheless, the Security and Exchange Commission of Brazil (CVM) has devised a strategic project to improve supervision, inspection and enforcement performance targeting primary insider traders.

On figure 8 we can observe the number of cases adjudicated related to insider trading and listed companies disclosures. This data was obtained from the CVM's annual reports, appendix A contains the complete table of adjudicated cases from 2011 to 2015. The 2016 annual report is not yet available at the time of writing.

The CVM's improvement measures were implemented in late 2015 and 2016. There is a considerable increase in the number of adjudicated cases related to insider trading and firm disclosure in 2015. It is important to highlight that the number of successful enforcement cases provides no direct information about the impact their securities commission is having on the level of market abuse.

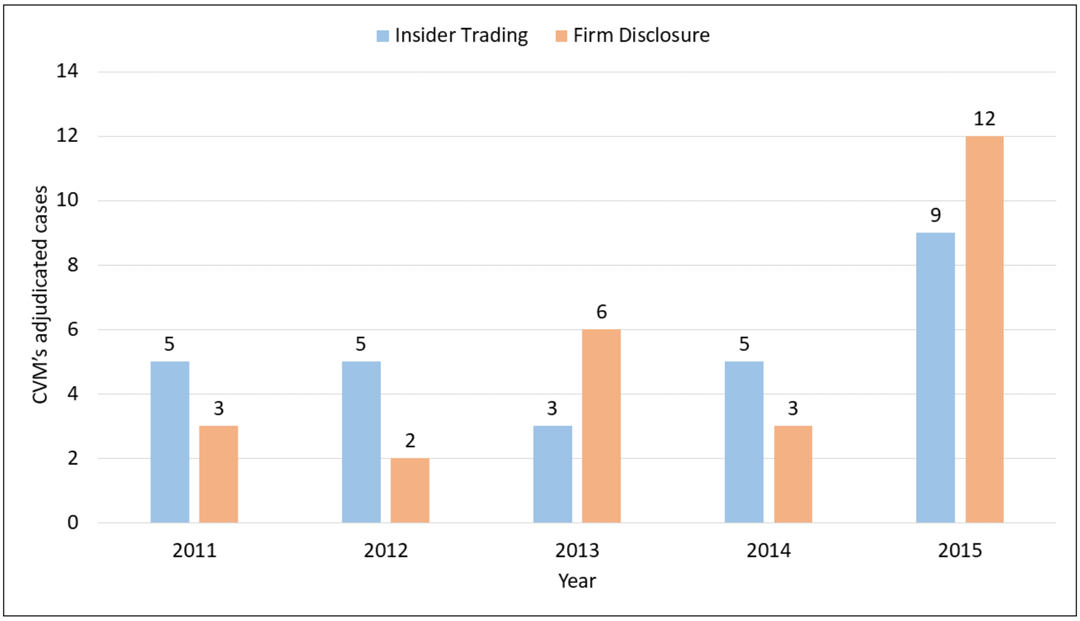


Figure 8 – CVM's adjudicated cases grouped by subject

However, the growth in adjudicated cases alone could have some deterrence effect, contributing to decreasing the attempts of informed trading. If perpetrators perceive to face higher chances of being detected, prosecuted and sanctioned, they would be less likely to engage in wrongdoing. According to IOSCO (2015), public messaging is crucial for credible deterrence because it demonstrates that "there are tangible consequences for those engaging or contemplating engagement in misconduct."

Considering Method B a superior measure of informed trading, the measurements indicate a decrease in informed trading from 2015 to 2016, 73.9% to 52.6%. Even though results from 2016 are still larger than from 2011 and 2012, the study suggests that informed trading started declining after the implementation of the CVM's strategic project that targets insider trading. It is premature to draw any conclusions about the deterrence effect of the measures at this point since the study only included one year after the project has started.

In addition, tt is difficult to precise when and how changes in the regulator's internal procedures affect enforcement cases, how long until those cases are adjudicated by the CVM and when or if they will cause any impact in the market. Therefore, the limited impact in informed trading levels could either mean that the strategic project had a modest impact on informed trading practices or that the impact has not fully produced effects yet due to the time lag for measures to reflect changes in the behavior of market participants and investors.

3 Conclusion

This study measured the level of informed trading in the Brazilian equity market by employing market cleanliness methodologies that solely utilize public data. Two market cleanliness methodologies have been applied to the same dataset in order to evaluate the methodologies and provided a systematic and comprehensive assessment of informed trading over time.

The second methodology labeled Method B offered superior results. Method B's conditional bootstrap seems to account for the circularity problem better than Method A's bias correction. Moreover, Method B's statistical models more suitably describe the asset behavior in 32.6% of the cases. Inferences results are more accurate.

Using Method B, this study results indicated high levels of informed trading when compared with the United Kingdom's (UK) and Australia's measurements. On average 58.2% of all significant announcements were preceded by informed price movements ahead of the listed companies' disclosure over the period of 2011 and 2016. Results suggest that trading with privileged information might be is a recurrent problem, undermining the Brazilian stock market's integrity and efficiency.

On the other hand, results displayed a modest decrease of levels of informed trading from 2015 to 2016. The Securities and Exchange Commission of Brazil (CVM) introduced its strategic project to improve its detection and enforcement capabilities of insider trading activities in late 2015 and 2016. Even though the measures adopted by the CVM appear to have generated positive deterrence effects, this study only included one year following the introduction of the measures.

Enforcement actions and administrative sanctions are time-consuming procedures. It is likely that outcomes derived from the project still have not fully manifested in investor and market participant behavior. In addition, as the strategic project focused on primary insiders, if the proportion of informed trading performed by primary insiders is much lower than secondary insiders, it is possible the impact on informed trading measurements and on market behavior can be attenuated. For that reason, further evidence from informed trading measurements in the coming years is necessary to draw conclusions about their overall impact of the project.

This study was able to establish a baseline for monitoring the deterrence effect of new regulatory frameworks regarding insider trading activity and firms disclosures. Moreover, it provides valuable information to investors to better understand market risks and conditions.

3.1 Policy Recommendations

Building on the analysis of the level of informed trading in Brazil, some specific recommendations are made to enhance market integrity and regulatory performance going forward.

One of the motivations for this study was verifying the feasibility of assessing market conditions solely using public data and an open source integrated development environment (RStudio), allowing anybody to replicate the analysis.

Market discipline improves with public participation. Investors could obtain more information about the market risks and conditions related to informed trading. This provides incentives to companies to better protect sensitive information.

Unfortunately, even though the data was free and technically available, it could not be efficiently extracted. For society to take advantage of all the benefits from open data, it is essential that all access restrictions to read, copy, share, and reuse public information be eliminated.

The Global Data Index's methodology, which assesses the quality of open data publications, only classifies data as "open data" if it is: available online without the need to register or request access, available free of charge, "downloadable at once", up-to-date, openly licensed or in public domain and available in open and machine-readable file formats. None of the data used for this study would be classified as "open data" according to this methodology.[1]

[1] It refers to the announcements data obtained from CVM's Office of Market Surveillance (SMI), the Ibovespa composition data obtained from BM&FBovespa S.A. and stocks adjusted price data from Bloomberg L.P. Although the stock price data published by BM&FBovespa could

Making data available stimulates the free-flow of information, enhances transparency, can help promote investor confidence, and promotes accountability. Improving data sharing empowers academics, investors, companies, other government bodies, and even other countries to produce information and knowledge that contributes to a more efficient, transparent, and fair market.

Since those outcomes are in line with the Securities and Exchange Commission of Brazil's Open Data Plan of 2016, the commission should ensure that all data that can be available to the public must be available as a whole in a convenient and modifiable form that can be efficiently interpreted, extracted, used, and redistributed. Moreover, sources of public data should allow automatic data extraction and open file formats whenever possible.

The second recommendation refers to the strategic program that was introduced by the regulator in 2015. Insider trading in securities markets has profound and pervasive consequences. Investors, capital markets, institutions, national economies, and global financial systems are all impacted when the integrity of markets are undermined. That is why one of the primary responsibilities of the regulator is to ensure that investors and market participants adopt fair trading practices.

According to this study, after the implementation of measures from this strategic program, the number of prosecuted cases have risen and a modest decline in informed trading levels was observed. Investigations and enforcement actions are resource-intensive and time-consuming. Consequently, most governmental entities must choose carefully how to focus their efforts.

It is critical that the regulator knows the current state of the market and can monitor how it is evolving as a response to its policies. This allows the regulator to set targets and course correct measures if necessary, thus ensuring resources are employed efficiently. Using the level of informed trading to evaluate the strategic program seems like a reasonable option. Therefore, future measurements of informed trading are necessary to evaluate the full impact of the project as well as oversee overall market behavior.

be classified as "open data" by this methodology, it is not adjusted for dividend distribution and stock splits.

3.2 Future Work and Research Limitations

Due to the scope limitations of this study, the impact of parameter changes was not tested. Future analyses could help improve this informed trading methodology by determining the optimal length of time for estimation, event and pre-event windows, inference significance level, and proper prediction model. Also, employing this methodology to markets from other countries could enhance our understanding of acceptable levels of informed trading and how to decrease it.

In addition, since the time and date of the announcements is available, future analysis could take into account the fact that announcements released after the stock exchange trading hours will only impact prices on the following day and adjust the event day. Moreover, future analysis should take into account clustering windows, i.e. if a company discloses more than one significant announcement on different days within the event window, informed trading measurements might provide incorrect results.

Some minor adjustments to the methodology could also contribute to improving the statistical properties of the models that describe asset behavior, providing more accurate inference results. Using logarithm returns instead of arithmetic returns should attenuate the skewness of residuals and allow the proper employment of cumulative average returns (CAR). Using the estimated variance from the equation (53) instead of (54) estimates asset's standardized abnormal returns more accurately. Applying GARCH(1,1) to all models regardless of the Engle's LM results should better account for changes in volatility between the estimation window and the event window.

This study identifies challenges and opportunities of utilizing data mining techniques as a cost-efficient strategy for market surveillance. Using bootstrap on residuals and inferences based on quantiles as described in this paper can be employed as a methodology for anomaly detection (outlier detection). This allows financial market regulators to monitor and detect suspicious price or volume movements, increasing not only enforcement productivity and quality but also helping to prioritize actions and support decision-making processes.

Abnormal prices or volumes not related to any announcement could potentially indicate insider trading activity, market manipulation, or inadequate disclosure practices. Abnormal prices or volumes related to announcements point to events of interest to an insider trader.

According to IOSCO (2015), an essential credible deterrence factor is market surveillance: "regulators make use of market surveillance and cyber surveillance technologies and teams to monitor the markets and the internet for early warning signs of misconduct, so that they can intervene rapidly in the interest of investors." As information about older events is not as easily available as recent news, the sooner a potential misconduct is recognized, the better the chances of finding relevant information to support the investigation. Besides, if investigated events are selected from a comprehensive systematic analysis, it decreases bias in enforcement actions. Moreover, a prompt response from the regulator also enforces the message to the market and investors that all trading activity is being monitored, which may discourage future attempts of misconduct.

Continued progress on developing these data mining methodologies for market surveillance can hinder the corrosive effects caused by impaired market integrity. Data-driven methods provide a comprehensive analysis that is less subjected to detection bias. Information provided by these methodologies can strengthen misconduct oversight from regulators as well as market participants and investors. This allows regulators to improve irregularities' detection mechanisms, build stronger evidence-based enforcement cases, respond faster to any suspicion of misconduct, ensure tangible consequences to noncompliance with regulation and violations of securities law, and enhance regulatory practices.

Appendix

A Appendix: CVM's adjudicated cases

The table below details the Securities and Exchange Commission of Brazil's (CVM) adjudicated cases grouped by subject. This information was published by CVM (2016b) on its annual report.

Table 6 – CVM's adjudicated cases

Subject	2011	2012	2013	2014	2015
Disclosures of relevant event/ acquisition of relevant participation	3	2	6	3	12
Periodic information disclosure	1	0	10	1	5
Market manipulation/ unfair market practices/ securities fraud	0	3	5	7	5
General assembly	0	3	10	6	4
Insider trading	5	5	3	5	9
Portfolio management and investment fund	0	0	2	0	4
Breach of fiduciary duty/ due diligence/ duty of secrecy	3	3	11	8	8
Audit	2	1	1	0	1
Others	13	14	30	23	25

B Appendix: Informed trading comparison using Method A

Method A attempts to replicate the methodology proposed by Dubow and Monteiro (2006). Table 7 displays the informed trading measurements obtained analyzing Brazilian data and the United Kingdom's data in different time periods.

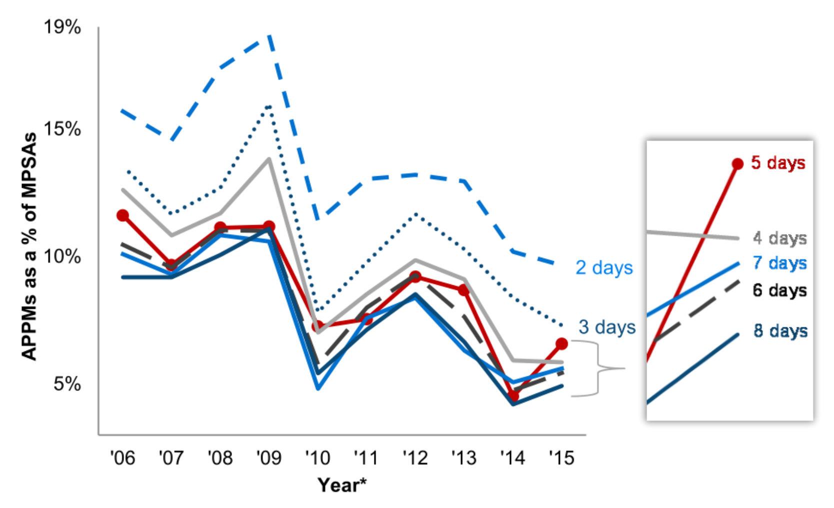
Table 7 – Brazil's and UK's informed trading - Method A

Period	Brazil
	Informed trading
2011	51.4%
2012	56.5%
2013	83.3%
2014	88.5%
2015	80.4%
2016	54.9%

Period	United Kingdom
	Maket Cleanliness*
1998/1999/2000	29.9%
2002/2003	30.7%
2004/2005	1.4%

* Values for UK FSA market cleanliness from Monteiro et al. (2007)

Method A is similar to the methodology described by ASIC (2016) for "2 days event window" (dashed blue line figure 9), where "APPMs as a percentage of MPSAs" is the measure of market cleanliness. Figure 9 displays the measurements obtained analyzing Australian data from 2006 to 31st October 2015.



* Year ended 31 October
Source: ASIC (2016)

Figure 9 – Australian market cleanliness

C Appendix: Brazil's and UK's informed trading using Method B

Method A attempts to replicate the methodology proposed by Monteiro et al. (2007), the table below displays the informed trading measurements obtained analyzing Brazilian data and the United Kingdom's data using the same methodology but in different time periods.

Table 8 – Brazil's and UK's informed trading - Method B

Period	Brazil
	Informed Trading
2011	50.0%
2012	46.7%
2013	61.5%
2014	63.0%
2015	73.9%
2016	52.6%

Period	United Kingdom
	Maket Cleanliness*
1998/1999/2000	19.6%
2002/2003	11.1%
2004/2005	2.0%

* Values for UK FSA market cleanliness from Monteiro et al. (2007)

D Appendix: Library versions of R packages

RStudio version 1.0.136 and R version 3.3.2 were used for the calculations used in this study. Below is a list of R packages' library versions used in the analysis.

Table 9 – Library versions of R packages

R Library		Description	Version
1.	dplyr	A grammar of data manipulation	0.5.0
2.	dynlm	Dynamic linear regression	0.3-5
3.	FinTS	Companion to Tsay (2005) analysis of financial times series	0.4-5
4.	lmtest	Testing linear regression models	0.9-35
5.	PerformanceAnalytics	Econometric tools for performance and risk analysis	1.4.3541
6.	rugarch	Univariate GARCH Models	1.3-6
7.	sandwich	Robust Covariance Matrix Estimators	2.3-4
8.	tidyr	Easily tidydata with spread() and gather() functions	0.6.1
9.	tseries	Time Series Analysis and Computational Finance	0.10-38
10.	xlsx	Read, write, format Excel 97/2000/XP/2003/2007 files	0.5.7
11.	xts	eXtensible Time Series	0.9-7

E Appendix: R scripts for Methods A and B

This code executes the analysis from Method A and B described in the subsections 2.2 and 2.3. The R scripts can also be found at this link.

```
#####################################################################
#                      Example for Method A                         #
#####################################################################

# Loading libraries
library(dplyr)
library(PerformanceAnalytics)
library(tseries)

# Create announcements dataframe
news_data <- data.frame(Company = c("OGXP", "OGXP", "OGXP",
                                    "PETR", "PETR","PETR"),
                        News.Date = as.Date(c("2012-06-28",
                                              "2013-10-31",
                                              "2013-12-06",
                                              "2014-12-07",
                                              "2014-11-18",
                                              "2015-04-13"),
                                              format = "%Y-%m-%d"))


# Create vector of asset tickers to be analysed
asset_tickers <- c("PETR3", "OGXP3")


# Create index time series
index_data = get.hist.quote(instrument="^BVSP",
                            start="2010-01-01",
                            end=Sys.Date(),
                            quote="AdjClose",
                            provider="yahoo",
                            compression="d",
                            retclass="zoo")
```

```
# Wrangling data: list of asset and index returns
list_returns <- lapply (X = asset_tickers,
                        FUN = Returns_calculation,
                        index_data = index_data)


# Calculation of Method A for retun data
methodA_results <- Reduce(rbind, lapply(X = list_returns,
                                        FUN = MethodA_analysis,
                                        announcements = news_data))


# Summary of Method A results
events = filter(methodA_results, obs %in% NA) %>%
 mutate(year = format(Announc_date, "%Y")) %>%
 group_by(event, year) %>%
 summarise(total_relevant=n()) %>%
 filter(event != "ok")

pre_events = filter(methodA_results, obs %in% NA) %>%
 mutate(year = format(Announc_date, "%Y")) %>%
 group_by(pre_event, year) %>%
 summarise(total_pre_event=n()) %>%
 filter(pre_event != "ok")

summary = full_join(events, pre_events, by="year") %>%
 mutate(proportion=total_pre_event/total_relevant)


# Bias correction
bias_results <- Reduce(rbind, lapply(X = list_returns,
                                     FUN = Bias_analysis,
                                     announcements = news_data))

bias_summary <- filter(bias_results, obs %in% NA) %>%
 mutate(year = format(Announc_date, "%Y")) %>%
 group_by(year) %>%
 summarise(mk = sum(false_sig_announc)/10000,
 total_false_IPM = sum(false_IPM)/10000,
 total_announc = n())
```

```
#####################################################################
#                    Functions for Method A                         #
#####################################################################

## Importing data, return calculation and data wrangling
Returns_calculation <- function (asset_name, index_data)
{
 # Example of asset data
 asset_xts <- xts(get.hist.quote(instrument = paste(asset_name,
                                                      sep = "",
                                                      ".SA"),
                                 start = "2010-01-01",
                                 end = Sys.Date(),
                                 quote="AdjClose",
                                 provider="yahoo",
                                 compression="d",
                                 retclass="zoo"))

 # Calculating asset return
 asset_returns <- Return.calculate(prices = asset_xts ,
                                   method = "discrete")


 # Calculating index return
 index_returns <- xts(Return.calculate(prices = index_data,
                                       method = "discrete"))
 # Merging asset and index returns
 returns <- na.omit(merge(x = asset_returns,
                          y = index_returns,
                          join = "left"))

 # Identifying the column with the asset name
 colnames(returns) <- c((paste(asset_name,
                        "return",
                        sep = "_")),
                       "index_return")
 return(returns)
}
```

```
## Market Model and UNCONDITIONAL bootstrap for Method A
MethodA_calculation <- function(relevant_date, asset_returns)
{
 # Extract estimation window and event window data
 prev_days <- xts::last(
   asset_returns[index(asset_returns) <= relevant_date], "250 days")
 next_day <- asset_returns[index(asset_returns) > relevant_date]

 # Stop function in case there is not enough data to apply model
 if (nrow(prev_days) < 250 | nrow(next_day) < 1)
    return(data.frame(Announc_date = relevant_date,
                      Upper_4CAR = NA , Lower_4CAR = NA,
                      CAR_4days = 0,
                      Upper_2CAR = NA,
                      Lower_2CAR = NA,
                      CAR_2days = 0,
                      obs = "not enough data for model estimation",
                      row.names = NULL))

 # Estimation window and event window data
 estimation_window <- first(prev_days, "240 days")
 event_window <- xts::last(rbind(prev_days, next_day[1]), "4 days")

 # Market Model over estimation window
 regression <- lm(estimation_window[,1] ~estimation_window[,2])

 # Calculating abnormal returns for the event window
 abnormal_returns_event <- c(event_window[,1] -
                             regression$coefficients[1] -
                             event_window[,2] *
                             regression$coefficients[2])
 CAR_4days <- sum(abnormal_returns_event)
 CAR_2days <- sum(abnormal_returns_event[1:2])

 # Calculating abnormal returns for the estimation window
 abnormal_returns <- c(estimation_window[,1] -
                       regression$coefficients[1] -
                       estimation_window[,2] *
                       regression$coefficients[2])
 colnames (abnormal_returns) <- "abnormal_returns"
```

```r
# Bootstrap 4 day CAR
bootstrap_input <- as.data.frame(abnormal_returns)
bootstrap_event <- replicate (10000,
                      sample(bootstrap_input$abnormal_returns,
                             4,replace = TRUE)) %>%
  t() %>%
  tbl_df() %>%
  mutate(CAR = V1+V2+V3+V4)
Upper_cutoff <- quantile(bootstrap_event$CAR, 0.995)
Lower_cutoff <- quantile(bootstrap_event$CAR, 0.005)

# Bootstrap 2 day CAR unconditional
bootstrap_pre_event <- replicate (10000,
                          sample(bootstrap_input$abnormal_returns,
                                 2, replace = TRUE)) %>%
  t() %>%
  tbl_df() %>%
  mutate(CAR2 = V1+V2)
Upper_cutoff_pre <- quantile(bootstrap_pre_event$CAR2, 0.95)
Lower_cutoff_pre <- quantile(bootstrap_pre_event$CAR2, 0.05)

# Output
out <- data.frame(Announc_date = relevant_date,
                  Upper_4CAR = Upper_cutoff,
                  Lower_4CAR = Lower_cutoff,
                  CAR_4days = CAR_4days,
                  Upper_2CAR = Upper_cutoff_pre,
                  Lower_2CAR = Lower_cutoff_pre,
                  CAR_2days = CAR_2days,
                  obs = NA,
                  row.names = NULL)

return(out)
}
```

```r
## Analyse announcements using Method A
MethodA_analysis <- function(asset_returns, announcements)
{
 # Extract the asset's name, company name, announcement dates
 asset_ticker <- strsplit(names(asset_returns)[1], "_")[[1]][1]
 asset_company_name <- substr(asset_ticker, start = 1 , stop = 4 )
 asset_announc_dates <- filter(.data = announcements,
                               Company == asset_company_name)

 # Stop function if there are no announcements for this asset
 if (nrow(asset_announc_dates) == 0)
     return(data.frame(Announc_date = NA, Upper_4CAR = NA,
                       Lower_4CAR = NA, CAR_4days = 0,
                       Upper_2CAR = NA, Lower_2CAR = NA,
                       CAR_2days = 0,
                       obs = "no announcements for this company",
                       event = NA, pre_event = NA,
                       asset = asset_ticker,
                       row.names = NULL))

 # Get all CAR limits for all announcements of this asset
 CAR_limits <- Reduce(rbind,
                  lapply(X = unique(asset_announc_dates$News.Date),
                  FUN = MethodA_calculation,
                  asset_returns = asset_returns ))

 # Classify if events/pre-events CAR are relevant
 CAR_analysis <- tbl_df(CAR_limits) %>%
   mutate(event = factor(ifelse(CAR_4days<Lower_4CAR |
                                CAR_4days>Upper_4CAR,
                                "relevant", "ok"))) %>%
   mutate(pre_event = factor(ifelse((CAR_2days<Lower_2CAR |
                                     CAR_4days>Upper_2CAR) &
                                     CAR_2days*CAR_4days>0 &
                                     event=="relevant",
                                     "IPM", "ok")))  %>%
   mutate(asset = asset_ticker)

 return(CAR_analysis)
}
```

```r
## Function for market model and bootstrap for bias correction
Bias_calculation <- function(relevant_date, asset_returns)
{
 # Extract estimation and event window data
 prev_days <- xts::last(
   asset_returns[index(asset_returns)<= relevant_date], "250 days")
 next_day <- asset_returns[index(asset_returns)> relevant_date]

 # Stop function in case there is not enough data to apply model
 if (nrow(prev_days)<250 | nrow(next_day)<1)
     return(data.frame(Announc_date = relevant_date,
                       false_sig_announc = NA, false_IPM = NA,
                       obs = "not enough data for model estimation",
                       row.names = NULL))

 # Estimation window and event window
 estimation_window = first(prev_days, "240 days")
 event_window = xts::last(rbind(prev_days, next_day[1]), "4 days")

 # Market Model over estimation window
 regression <- lm(estimation_window[,1] ~estimation_window[,2])

 # Calculate abnormal returns for the estimation window
  abnormal_returns = c(estimation_window[,1] -
                       regression$coefficients[1] -
                       estimation_window[,2] *
                       regression$coefficients[2])
 colnames (abnormal_returns)= "abnormal_returns"

 # Bootstrap 4 day CAR
 bootstrap_input = as.data.frame(abnormal_returns)
 bootstrap_event= replicate (10000,
                       sample(bootstrap_input$abnormal_returns,
                              4, replace = TRUE)) %>%
   t() %>%
   tbl_df() %>%
   mutate(CAR = V1+V2+V3+V4)
 Upper_cutoff = quantile(bootstrap_event$CAR, 0.995)
 Lower_cutoff = quantile(bootstrap_event$CAR, 0.005)
```

```r
 # Bootstrap 2 day CAR unconditional
 bootstrap_pre_event= replicate (10000,
                         sample(bootstrap_input$abnormal_returns,
                                2, replace = TRUE)) %>%
   t() %>%
   tbl_df() %>%
   mutate(CAR2 = V1+V2)
 Upper_cutoff_event = quantile(bootstrap_pre_event$CAR2, 0.95)
 Lower_cutoff_event = quantile(bootstrap_pre_event$CAR2, 0.05)

 # Bootstrap bias correction simulation of event
 bootstrap_bias= replicate (10000,
                    sample(bootstrap_input$abnormal_returns,
                           4, replace = TRUE)) %>%
   t() %>%
   tbl_df() %>%
   mutate(CAR = V1+V2+V3+V4) %>%
   filter(CAR>Upper_cutoff | CAR<Lower_cutoff) %>%
   mutate(CAR2 = V1+V2)
 aux_bias = bootstrap_bias %>%
   filter(CAR2>Upper_cutoff_event | CAR2<Lower_cutoff_event) %>%
   filter(CAR*CAR2>0)
 fake_sig_announc = nrow(bootstrap_bias)
 fake_sig_pre = nrow(aux_bias)

 # Output
 out= data.frame(Announc_date = relevant_date,
                 false_sig_announc = fake_sig_announc,
                 false_IPM = fake_sig_pre,
                 obs = NA)

 return(out)
}
```

```r
## Function to calculate bias correction in Method A
Bias_analysis <- function(asset_returns, announcements)
{
 # Extract the asset's name, company name, announcement dates
 asset_ticker <-strsplit(names(asset_returns)[1], "_")[[1]][1]
 asset_company_name <- substr(asset_ticker, start=1 , stop= 4 )
 asset_announc_dates <- filter(announcements,
                               Company==asset_company_name)

 # Stop function if there are no announcements for this asset
 if (nrow(asset_announc_dates)==0)
    return(data.frame(Announc_date = NA,
                      false_sig_announc = NA,
                      false_IPM = NA,
                      obs="no announcements for this company",
                      asset=asset_ticker,
                      row.names = NULL))

 # Get all CAR limits for all announcements of this asset
 CAR_limits <- Reduce(rbind,
                  lapply(unique(asset_announc_dates$News.Date),
                               FUN = Bias_calculation,
                               asset_returns = asset_returns)) %>%
   mutate(asset=asset_ticker)

 return(CAR_limits)
}
```

```r
##################################################################
#                    Example for Method B                        #
##################################################################

# Loading libraries
library(dplyr)
library(xts)
library(lmtest)
library(dynlm)
library(sandwich)
library(FinTS)
library(rugarch)
library(tseries)
library(PerformanceAnalytics)

# Create announcements dataframe
news_data <- data.frame(Company = c("OGXP", "OGXP", "OGXP",
                                    "PETR", "PETR","PETR"),
                        News.Date = as.Date(c("2012-06-28",
                                              "2013-10-31",
                                              "2013-12-06",
                                              "2014-12-07",
                                              "2014-11-18",
                                              "2015-04-13"),
                                              format = "%Y-%m-%d"))


# Create vector of asset tickers to be analysed
asset_tickers <- c("PETR3", "OGXP3")


# Create index time series
index_data = get.hist.quote(instrument="^BVSP",
                            start="2010-01-01",
                            end=Sys.Date(),
                            quote="AdjClose",
                            provider="yahoo",
                            compression="d",
                            retclass="zoo")
```

```r
# Wrangling data: list of asset and index returns
list_returns <- lapply (X = asset_tickers,
                        FUN = Returns_calculation,
                        index_data = index_data)


# Calculation of Method A for retun data
methodB_results <- Reduce(rbind, lapply(X = list_returns,
                                        FUN = MethodB_analysis,
                                        announcements = news_data))

# Summary of Method B results
events <- methodB_results %>%
 filter(!(obs1 %in% "not enough data for model estimation")) %>%
 filter(!(obs1 %in% "no announcements for this company")) %>%
 mutate(year = format(Announc_date, "%Y")) %>%
 group_by(event, year) %>%
 summarise(total_relevant=n()) %>%
 filter(event != "ok")

pre_events <- methodB_results %>%
 filter(!(obs1 %in% "not enough data for model estimation")) %>%
 filter(!(obs1 %in% "no announcements for this company")) %>%
 mutate(year = format(Announc_date, "%Y")) %>%
 group_by(pre_event, year) %>%
 summarise(total_IPM = n()) %>%
 filter(pre_event != "ok")

summary = full_join(events, pre_events, by="year" ) %>%
 mutate(proportion = total_IPM/total_relevant)


####################################################################
#                   Functions for Method B                        #
####################################################################

## Importing data, return calculation and data wrangling
Returns_calculation <- function (asset_name, index_data)
{
```

```
 # Example of asset data
 asset_xts <- xts(get.hist.quote(instrument = paste(asset_name,
                                                    sep = "",
                                                    ".SA"),
                              start = "2010-01-01", end = Sys.Date(),
                              quote="AdjClose", provider="yahoo",
                              compression="d", retclass="zoo"))

 # Calculating asset return
 asset_returns <- Return.calculate(prices = asset_xts ,
                                    method = "discrete")

 # Calculating index return
 index_returns <- xts(Return.calculate(prices = index_data,
                                        method = "discrete"))
 # Merging asset and index returns
 returns <- na.omit(merge(x = asset_returns,
                          y = index_returns,
                          join = "left"))

 # Identifying the column with the asset name
 colnames(returns) <- c((paste(asset_name,
                         "return",
                         sep = "_")),
                        "index_return")
 return(returns)
}

# Asset model, check for heteroskedasticity and serial correlation
Model_tests <- function(returns, window)
{
 # Periods for calculation
 estimation <- first(window, "240 days")
 event <- xts::last(window, "4 days")

 # Linear Model for estimation window
 reg <- lm(estimation[,1] ~estimation[,2])
```

```
# Durbin's alternative  test for serial correlation
aux_df <- estimation
aux_df$res <- reg$residuals
aux_df$res_lag <- lag(aux_df$res, k = 1)
aux_df1 <- as.zoo( na.omit(aux_df))
aux_reg_sc <- with (aux_df1,
                   dynlm(formula = res ~ res_lag +
                              index_return))
wald_t <- waldtest(aux_reg_sc ,1 ,
                   test = "Chisq", vcov = vcovHC)

# Engle LM test for ARCH(1) for heteroskedasticity
arch_t <- ArchTest(as.zoo(residuals(reg)), lags=1)

# Select model
if(wald_t$`Pr(>Chisq)`[2] > 0.05 & arch_t$p.value > 0.05) {

  # No serial correlation, no heteroskedasticity
  tests <- c("no_sc_no_hk", NA)

  # Abnormal returs from linear regression
  AR_estimation <- residuals(reg)
  AR_event <- c(event[,1] -
              reg$coefficients[1] -
            event[,2] * reg$coefficients[2])

  out <- list(tests, AR_estimation, AR_event)
  return(out)

} else if(wald_t$`Pr(>Chisq)`[2] > 0.05 & arch_t$p.value <= 0.05) {

  # No serial correlation, heteroskedasticity
  tests <- "no_sc_hk"

  # Linear regression, GARCH(1,1)
  fit.spec <- ugarchspec(variance.model = list(model = "sGARCH",
                                          garchOrder = c(1, 1)),
                       mean.model = list(armaOrder = c(0, 0),
                                include.mean = TRUE,
                                external.regressors = window[,2]))
```

```r
  # Estimates the model excluding last 11 observations
  fit <- ugarchfit(spec = fit.spec,
                   data = window[,1],
                   out.sample=11,
                   solver = "hybrid")

  # Standardized abnormal returns for estimation window
  AR_estimation <- (estimation[,1]-fitted(fit))/sigma(fit)

  # Expected sigma and abnormal return of event window
  expected_sigma <- xts::last(sigma(fit))
  for (nrow in 1:11) {
    expected_sigma_t_plus1 <- sqrt(coef(fit)[3] +
                                   coef(fit)[5] *
                                   xts::last(expected_sigma)^2)
    expected_sigma <- rbind(expected_sigma,
                            expected_sigma_t_plus1)
    }
  expected_sigma <- as.numeric(coredata(expected_sigma[9:12]))
  expected_AR <- event[,1] - coef(fit)[1] -
                 coef(fit)[2] * event[,2]

  # Standardized abnormal returns for event window
  AR_event <- expected_AR/expected_sigma

  # Engle LM test for ARCH(1) for heteroskedasticity
  arch_t_pos <- ArchTest(residuals(fit, standardize=TRUE), lags=1)

  # Test results after changing model
  tests[2] <- ifelse (arch_t_pos$p.value <= 0.05,
                     "still hk", "no more hk")

  out = list(tests, AR_estimation, AR_event)
  return(out)

} else if(wald_t$`Pr(>Chisq)`[2] <= 0.05 & arch_t$p.value > 0.05) {

  # Serial correlation, no heteroskedasticity
  tests <- "sc_no_hk"
```

```
  # ADL model
  input_sc <- estimation
  input_sc$asset_lag <- lag(input_sc[,1], k=1 )
  input_sc$index_lag <- lag(input_sc[,2], k=1 )
  input_sc <- na.omit(input_sc)
  model_sc <- lm(input_sc[,1] ~ input_sc[,2] +
                               input_sc[,3] +
                               input_sc[,4] )

  # Abnormal returns
  AR_estimation <- residuals(model_sc)
  AR_event <- c(event[,1] - model_sc$coefficients[1] -
                event[,2] * model_sc$coefficients[2])

  # Durbin's alternative test for serial correlation
  aux_df <- estimation
  aux_df$res <- model_sc$residuals
  aux_df$res_lag <- lag(aux_df$res, k = 1)
  aux_df <- as.zoo( na.omit(aux_df))
  aux_reg_sc <- with (aux_df,
                    dynlm(formula = res ~ res_lag +
                          index_return))
  wald_t_pos <- waldtest(aux_reg_sc ,1 ,
                       test = "Chisq", vcov = vcovHC)

  # Test results after changing model
  tests[2] <- ifelse (wald_t_pos$`Pr(>Chisq)`[2] <= 0.05,
                    "still sc", "no more sc")

  out <- list(tests, AR_estimation, AR_event)
  return(out)

} else {

  # There is serial correlation and heteroskedasticity
  # ADL model
  lag_aux <- lag(returns[,2], 1)
  input_xreg <- na.omit(as.matrix(cbind(window[,2], lag_aux)))
```

```r
# ADL-GARCH(1,1) model specification
fit.spec <- ugarchspec(variance.model = list(model = "sGARCH",
                                              garchOrder = c(1, 1)),
                       mean.model = list(armaOrder = c(1, 0),
                              include.mean = TRUE,
                              external.regressors = input_xreg))

# Estimates the model excluding last 11 observations
fit <- ugarchfit(spec = fit.spec,
                 data = window[,1],
                 out.sample=11,
                 solver = "hybrid")

# Standardized abnormal returns for estimation window
AR_estimation <- (estimation[,1]-fitted(fit))/sigma(fit)

# Expected sigma and abnormal return of event window
expected_sigma <- xts::last(sigma(fit))
for (nrow in 1:11) {
  expected_sigma_t_plus1 <- sqrt(coef(fit)[3] +
                            coef(fit)[5] *
                            xts::last(expected_sigma)^2)
   expected_sigma <- rbind(expected_sigma,expected_sigma_t_plus1)
   }
expected_sigma <- as.numeric(coredata(expected_sigma[9:12]))
expected_AR <- event[,1] - coef(fit)[1] -
               coef(fit)[2]*event[,2]

# Standardized abnormal returns for event window
AR_event <- expected_AR/expected_sigma

# Engle LM test for ARCH(1) for heteroskedasticity
arch_t_pos <- ArchTest(as.zoo(
              residuals(fit, standardize = TRUE)), lags = 1)
tests <- ifelse (arch_t_pos$p.value <= 0.05,
                 "still hk", "no more hk")
```

```r
    # Durbin's alternative  test for serial correlation
    aux_df <- estimation
    aux_df$res <- residuals(fit)
    aux_df$res_lag <- lag(aux_df$res, k = 1)
    aux_df <- as.zoo( na.omit(aux_df))
    aux_reg_sc <- with ( aux_df,
                        dynlm(formula = res ~ res_lag +
                              index_return))
    wald_t_pos <- waldtest(aux_reg_sc ,1 ,
                           test = "Chisq", vcov = vcovHC)

    # Test results after changing model
    tests[2] <- ifelse(wald_t_pos$`Pr(>Chisq)`[2] <= 0.05,
                       "still sc", "no more sc")

    out <- list(tests, AR_estimation, AR_event)
    return(out)
  }
}

## Asset model and CONDITIONAL bootstrap for Method B
MethodB_calculation <- function(relevant_date, asset_returns)
{
 # Extract estimation window and event window data
 prev_days <- xts::last(
  asset_returns[index(asset_returns) <= relevant_date], "250 days")
 next_day <- asset_returns[index(asset_returns) > relevant_date]

 # Stop function in case there is not enough data to apply model
 if (nrow(prev_days) < 250 | nrow(next_day) < 1)
  return(data.frame(Announc_date = relevant_date,
                    Upper_4CAR = NA ,
                    Lower_4CAR = NA,
                    CAR_4days = 0,
                    Upper_2CAR = NA,
                    Lower_2CAR = NA,
                    CAR_2days = 0,
                    obs1 = "not enough data for model estimation",
                    obs2 = NA,
                    row.names = NULL))
```

```r
# Estimation window and event window
asset_returns_window <- rbind(prev_days, next_day[1])
estimation_window <- first(asset_returns_window, "240 days")
event_window <- xts::last(asset_returns_window, "4 days")

#Tests of Serial Correlation and Heteroskedasticity
tests_results <- Model_tests(returns = asset_returns,
                             window = asset_returns_window)

# Calculate abnormal returns for the event window
abnormal_returns_event <- tests_results[[3]]
CAR_4days <- sum(abnormal_returns_event)
CAR_2days <- sum(abnormal_returns_event[1:2])

# Calculate abnormal returns for the estimation window
abnormal_returns_240 <- tests_results[[2]]

# Bootstrap 4 day CAR
bootstrap_input <- as.data.frame(abnormal_returns_240)
bootstrap_event <- replicate (50000,
                              sample(bootstrap_input[,1],
                              4, replace = TRUE)) %>%
  t() %>%
  tbl_df() %>%
  mutate(CAR = V1+V2+V3+V4)
Upper_cutoff = quantile(bootstrap_event$CAR, 0.995)
Lower_cutoff = quantile(bootstrap_event$CAR, 0.005)

# If the event is relevant, verify pre-event
if(CAR_4days < Lower_cutoff | CAR_4days > Upper_cutoff) {
  # Bootstrap 2 day CAR conditional
  bootstrap_pre_event <- replicate (50000,
                                    sample(bootstrap_input[,1],
                                           4, replace = TRUE)) %>%
     t() %>%
     tbl_df() %>%
     mutate(CAR = V1+V2+V3+V4) %>%
     filter(CAR > Upper_cutoff| CAR < Lower_cutoff) %>%
     mutate(CAR2 = V1+V2)
```

```r
    Upper_cutoff_event <- quantile(bootstrap_pre_event$CAR2, 0.90)
    Lower_cutoff_event <- quantile(bootstrap_pre_event$CAR2, 0.10)

  } else {

    Upper_cutoff_event <- NA
    Lower_cutoff_event <- NA
  }

  # Output
  out = data.frame(Announc_date = relevant_date,
                   Upper_4CAR = Upper_cutoff,
                   Lower_4CAR = Lower_cutoff,
                   CAR_4days = CAR_4days,
                   Upper_2CAR = Upper_cutoff_event,
                   Lower_2CAR = Lower_cutoff_event,
                   CAR_2days = CAR_2days,
                   obs1 = tests_results[[1]][1],
                   obs2 = tests_results[[1]][2],
                   row.names = NULL)
  return(out)
}


## Analyse announcements using Method B
MethodB_analysis <- function(asset_returns, announcements)
{
  # Extract the asset's name, company name, announcement dates
  asset_ticker <-strsplit(names(asset_returns)[1], "_")[[1]][1]
  asset_company_name <- substr(asset_ticker, start = 1 , stop = 4 )
  announc_dates <- filter(announcements,
                              Company==asset_company_name)

  # Stop function if there are no announcements for this asset
  if (nrow(announc_dates) == 0)
    return(data.frame(Announc_date = NA,
                      Upper_4CAR = NA ,
                      Lower_4CAR = NA,
                      CAR_4days = 0,
                      Upper_2CAR = NA,
```

```
                      Lower_2CAR = NA,
                      CAR_2days = 0,
                      obs1 = "no announcements for this company",
                      obs2 = NA,
                      event = NA,
                      insider = NA,
                      asset = asset_ticker,
                      row.names = NULL))

# Get all CAR limits for all announcements of this asset
asset_CAR_limits <- Reduce(rbind,
                     lapply(X = unique(announc_dates$News.Date),
                            FUN = MethodB_calculation,
                            asset_returns = asset_returns))

# Classify if events/pre-events CAR are relevant
CAR_analysis <- tbl_df(asset_CAR_limits) %>%
  mutate(event = factor(ifelse(CAR_4days < Lower_4CAR |
                                 CAR_4days > Upper_4CAR,
                               "relevant", "ok"))) %>%
  mutate(pre_event = factor(ifelse((CAR_2days < Lower_2CAR |
                                      CAR_4days > Upper_2CAR) &
                                      CAR_2days*CAR_4days > 0 &
                                      event == "relevant",
                                      "IPM", "ok")))  %>%
  mutate(asset = asset_ticker)

return(CAR_analysis)
}
```

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