

ROSARIO UNIVERSITY

**Synthetic portfolio for event studies:
Estimating the effects of volatility call
auctions**

by

Sergio Preciado

A thesis submitted in partial fulfillment for the
degree of Master in Quantitative Finance

in the
Faculty of Economics

July 2016

ROSARIO UNIVERSITY

Abstract

Faculty of Economics

Master in Quantitative Finance

by Sergio Preciado

We propose a method denoted as synthetic portfolio for event studies in market microstructure that is particularly interesting to use with high frequency data and thinly traded markets. The method is based on Synthetic Control Method and provides a robust data driven method to build a counterfactual for evaluating the effects of the volatility call auctions. We find that SMC could be used if the loss function is defined as the difference between the returns of the asset and the returns of a synthetic portfolio. We apply SCM to test the performance of the volatility call auction as a circuit breaker in the context of an event study. We find that for Colombian Stock Market securities, the asynchronicity of intraday data reduces the analysis to a selected group of stocks, however it is possible to build a tracking portfolio. The realized volatility increases after the auction, indicating that the mechanism is not enhancing the price discovery process.

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Chapter 1

Introduction

Circuit breakers are mechanisms implemented in trading platforms at stock exchanges to provide time for agents to assimilate new information in a continuous trading environment in order to enhance the price discovery process. There is no consensus with respect to the need and the effectiveness of circuit breakers.

The literature has discussed whether it is better to have price halts, price limits or not having any at all, and their effects on Market Quality, Subrahmanyam (1994) studied the trading halts in the NYSE, where if the Dow Jones moved by more than 250 or 400 points in a one or two hours period respectively then the market was halted for a stipulated period of time. In his study he concluded that trading halts may actually increase price variability. Christie et al, (2002) suggest that high levels of volatility were sustained for longer periods of time due to the halt. This effect could be due to the fact that during the halt there is no trading, then individuals cannot absorb information efficiently and therefore uncertainty increases, also slowing down the price discovery process. Madhavan (1992) shows that during periods of severe information asymmetries, a continuous market may not be viable, and that once a market is halted it may be difficult to restart the trading process.

Circuit breakers can have different designs that may be used simultaneously, the two most common types of circuit breakers are (discretionary) trading halts and price limits. A trading halt is activated when prices have moved or will imminently move by some specific amount; trading will be halted until a specific amount of time (an hour or the next day) or until the order imbalance is resolved (possibly by means of a call auction). Price limits are introduced to force traders to deal within a certain range. Whereas price limits have had a long tradition, specially in future markets trading halts started to be widely used since Black Monday, October 1987.

In particular we are interested in a type of circuit breakers known as a volatility call auctions. The design of such circuit breaker is as follows: there is a predefined upper and lower bounds for prices (bounds are set in accordance to the historical liquidity for the asset and a current reference price), if in a continuous trading environment a buy or sell order is submitted above or below the bounds then a call auction is activated lasting approximately two and a half minutes, with a random thirty second closing time. During the call auction the order that initiates the call auction cannot refrain from participating and can only submit a better price. In general during the time of the auction the clearing price is public but the order book is not, in this way individuals have more information about the impact of the event that triggered the circuit breaker. Finally when the auction ends, the continuous trading session goes on, unless another volatility auction is initialized.

Stock specific circuit breaking mechanisms like the volatility call auctions are more commonly used European stock exchanges in particular the Spanish Stock Exchange than US stock exchanges. Reboredo (2010) studied the effect of volatility call auctions in the Spanish Stock Exchange (SSE) finding that the decrease in volatility following volatility auctions is stronger than in the absence of the auction, on the other hand, that volatility auctions provide for new information to be quickly incorporated in prices. He also concludes that the bid-ask spread widens before an auction, this result goes in line to Madhavan (1992) proposition that the switch that activates the auction should be the bid-ask spread and not the volatility. Abad and Pascual (2010) also examine this mechanism for the SSE, they find that volatility, trading activity and illiquidity remains high for around ninety minutes after continuous trading resumes. However they mention that as in previous studies a major drawback is the lack of an appropriate comparison, that is the lack of a proper counterfactual does not allow to answer the following question: What would be the behavior of the specific stock had the volatility auction not taken place?

In order to examine the effectiveness of such a mechanism we follow an event study approach using high frequency quote data. The event in question is the period during which continuous trading halts and the volatility auction mechanism is put in place (around two and a half minutes). Our objective is to measure the effect of the mechanism with respect to returns and volatility. As in any event study we use the period before the event in order to come up with a proper counterfactual that we will use in the post event window to measure the effect of the mechanism.

We propose a method denoted as synthetic portfolio for event studies in market microstructure that is particularly interesting to use with high frequency data and thinly traded markets. The main advantage of the synthetic portfolio method is that it provides a robust data driven method to build a counterfactual and it is derived from a well established techniques, synthetic control method for comparative case studies, Abadie, et al. (2010). Although a synthetic portfolio approach has already been used in the literature Guidolin and La Ferrara (2007), Castañeda and Vargas (2012), Acemoglu et al. (2015) to the best of our knowledge this is the first paper that documents its relationship to synthetic control methods and established methodological affinities to the standard event study techniques pioneered by Brown and Warner (1985) and reviewed by MacKinlay (1997).

Our contribution is both methodological by proposing the synthetic portfolio approach for event studies and empirical by applying such technique to evaluate the effectiveness of a volatility call auction as a circuit breaker using intra day data.

We use intraday data of 45 assets listed in the Colombian Stock Exchange (Bolsa de Valores de Colombia - BVC) from august 2010 to august 2012. The data contains bid and ask quotes, trades, and also the time when a volatility auction was triggered and when it finished. In total there are 1062 volatility auctions in our time window.

Our are results mixed we find that for Colombian Stock Market securities, the asynchronicity of intraday data reduces the analysis to a selected group of stocks, nevertheless it is possible to find weights that could provide and accurate synthetic portfolio that replicates the returns of a security affected by a volatility auction. The realized volatility increases after the auction, indicating that the mechanism is not enhancing the price discovery process by reducing volatility.

Chapter 2

Database and sample

In 2009 the Bolsa de Valores de Colombia (BVC), the Colombian Stock Exchange, changed the stock trading platform. The new platform incorporated features such as volatility call auctions. In the Colombian case stocks have price limits defined using deviations of the closing price of the previous day of trading, according to the volatility there are three price intervals (6.5%, 5.5%, and 4%), each asset is classified in one group in function of its own volatility. If during the continuous trading session the platform identifies the possibility of a match outside or in the price limits a volatility auction is set in place. As soon as it starts all the orders that were placed before are withdrawn from the book, the auction last for two and a half minutes and has a 30 seconds random closure. When the auction ends the equilibrium price is calculated, as the one that maximizes trading volume. Depending on the new reference price the price limits are recalculated, therefore any order submitted at the auction that has prices out of the new limits are eliminated. In the BVC there are no limits to the number of volatility auctions and an auction can start in the very moment that another auction ends. It does not matter the size of the order that starts the auction, but the order that causes the auction cannot be canceled until the end of the auction (Figure 5.1).

Our data is composed of 45 assets listed in the Colombian Stock Exchange (Bolsa de Valores de Colombia - BVC) from august 2010 to august 2012. The data contains bid and ask quotes, trades, and also the time where a volatility auction was triggered and when it finished. In total there are 1062 volatility auctions, this auctions are triggered at any time of the day and about 90% are concentrated in no more than 19 assets as seen in figure 5.3. We narrowed down the analysis to a group of 8 assets (ECOPETL, ENKA, EXITO, FABRI, INVARGOS, ISA, PFBCOLO, and PREC). The BVC defines different liquidity groups for stocks. Our selection is based on the assets that belonged to the high liquidity group defined by the BVC for our time window, this group is redefined

every quarter. Finally a set of auctions where selected according to differents criterias in chapter 4.

Chapter 3

Synthetic portfolio approach for event studies

The synthetic control method (Abadie, et al. 2010), (SCM) has received a lot of attention in comparative case studies on different subjects: terrorism, natural disasters, tobacco control programs. As opposed to competing methods SCM strength relies in the use of a combination of units to built a more objective comparison for the unit exposed to the intervention, rather than a choosing a single unit.

The SCM is a weighted average of the available control units, that makes explicit: the contribution of each unit to the counterfactual of interest and the similarities (or lack thereof) between the unit affected by the event or the intervention of interest and the syntectic control in terms of the pre-intervention outcomes and other predictors of post-intervention outcomes.

We are not aware of the use of SCM in event studies (comparative case studies) in finance. In our case we have an intervention: the volatility action that effects at least one security in the market. Let T_0 denote the starting time of the volatility auction. The available data is intra-day data of the securities of interest $Y_{i,t}$ for security $i = 1, \dots, J$ and $t = 1, \dots, T$, where $T_0 < T$. Suppose that security 1 is the only one affected by the intervention. Let $Y_{i,t}^N$ ($Y_{i,t}^I$) denote the outcome that would be (is) observed for security i if the volatility auction had not taken (takes) place at time T_0 . Note that $Y_{i,t}^N$ is a latent variable and $Y_{i,t}^I$ is the observed outcome for the variable of interest after the intervention ($T_0 < t < T$); then $\alpha_{i,t} = Y_{i,t}^I - Y_{i,t}^N$ it the effect of the intervention for unit i at time $t \in (T_0, T]$. Abadie et al. (2010) proposes the following estimate for the effect

of the intervention,

$$\hat{\alpha}_{1,t} = Y_{1,t} - \sum_{j=2}^J w_j^* Y_{j,t} \quad (3.1)$$

where w_j^* is obtained by imposing a series of restrictions on the data generating process with respect to $Y_{i,t}^N$ and the tractability of the other units to the outcome of the unit of interest in the pre-intervention period.

Suppose there exist a vector of weights $\mathbf{W} = (w_2^*, \dots, w_J^*)$ such that

$$\left(\begin{array}{l} \sum_{j=2}^J w_j^* Y_{j,1} = Y_{1,1}, \quad \sum_{j=2}^J w_j^* Y_{j,2} = Y_{1,2} \\ \sum_{j=2}^J w_j^* Y_{j,T_0} = Y_{1,T_0} \quad \text{and} \quad \sum_{j=2}^J w_j^* \mathbf{Z}_j = \mathbf{Z}_1 \end{array} \right) \quad (3.2)$$

Where \mathbf{Z} denote a vector of observed covariates that are part of the data generating process of $Y_{i,t}^N$, along with other non-observable components. However, the existence or use of this set of covariates is not essential for the SCM to work. Although some restrictions on the weights and the use of covariates can provide a safeguard against extrapolation or data-snooping as discussed in Abadie et al 2010.

Since the estimate of the effect of the intervention and in particular the synthetic control, 3.1 is a weighted average of the available control units; its application in finance is equivalent to building a synthetic benchmark with a different purpose than the usual.

The purpose of tracking and index with a couple of securities is to setup a passive investment strategy the follows the performance of a popular index, like the S&P500. Therefore the idea is to choose a set of securities and find the weights that minimize the replication or tracking error. In analogy to a standard portfolio problem we must define an objective function and specify the relevant constrains for the problem. A simple objective function is the the average of the deviations of the tracking portfolio returns from the index returns over the period of time (Gilli and Kellezi, 2002).

$$R_{1,T_0} = \frac{\sum_{t=1}^{T_0} \mathbf{W} \mathbf{R}_t - r_t^{\text{index}}}{T_0 - 1} \quad (3.3)$$

Where \mathbf{W} is a vector of weights for the J assets, \mathbf{R}_t is the vector of observed returns at time t, and r_t^{index} is the return of the index.

In our proposed methodology for event studies the index would be $Y_{1,t}$ the security of interest where we want to measure the effect of the intervention. In other words the security whose trading had been halted because of the volatility auction mechanism. On the other hand the syntectic control is build by using the other securities (those in continuous trading, before, during and after the intervention) to replicate the performance

of the security of interest.

The methodology is very simple since we only need to obtain w_j^* required to estimate the effect of the intervention in 3.1 by solving the tracking problem. Therefore we have to solve,

$$\mathbf{w}^* = \underset{\mathbf{w}}{\operatorname{argmin}} \sum_{t=1}^{T_0} \left(Y_{1,t} - \sum_{j=2}^J w_j Y_{j,t} \right)^2 \quad (3.4)$$

This would be for the pre-intervention period $t \in [1, T_0)$. A proper tracking of the security of interest (security 1) would guarantee that the synthetic control is a proper counterfactual. We denote this synthetic control as a synthetic portfolio (SP) that is a proper counterfactual.

With the post-intervention data we would estimate the desired effect.

$$\hat{\alpha}_{1,t} = Y_{1,t} - \sum_{j=2}^J w_j^* Y_{j,t}, t \in (T_0, T] \quad (3.5)$$

The outcome variable $Y_{i,t}$ is determined based on the effect we are interested in analyzing: trading activity (number of trades), liquidity (bid and ask price), and for returns and volatility (returns). In this last case where $Y_{i,t} := R_{i,t}$ it is possible to determine a relationship between the synthetic control method we propose and the traditional procedure for event studies.

For traditional event studies we have a similar set-up, with respect to the time index, t : pre-event or estimation window $t \in [1, T_0)$ and an event window $t = T_0$ and a post-event window $t \in [T_0, T)$. However, in our particular setup the estimation of the variables of interest is done in the post-event window rather than the event window. Using the notation of event studies the abnormal returns of the asset of interest (asset 1) are equivalent to $\hat{\alpha}_{1,t}$.

$$\hat{\alpha}_{1,t} := AR_{1,t} = R_{1,t} - \sum_{j=2}^J w_j^* R_{j,t}, t \in (T_0, T] \quad (3.6)$$

This expression is similar to the definition of abnormal returns where the normal performance (the counterfactual in traditional event studies) is defined by a constant mean return model (Figure 5.2).

$$AR_{1,t} = R_{1,t} - \frac{1}{T - T_0} \sum_{t=T_0+1}^T R_{1,t} \quad (3.7)$$

The important difference is that the abnormal returns in the traditional event studies are based on the difference between the observed returns of the asset and the simple time average of the returns of the same asset over the event window. In the case of the synthetic portfolio the abnormal returns are based on the difference between the observed returns of the asset and a weighted average of the returns of all other asset available that were not affected by the event of interest. After we obtain the abnormal returns we can estimate the cumulative abnormal returns $CAR_1(T_0, T) = \sum_{t=T_0+1}^T AR_{1,t}$. In order to analyse the effects on volatility we can obtain realized volatility estimates for the returns of the asset and also for the returns of the synthetic portfolio over the post-event window.

In traditional event studies there is another possibility to define the normal performance, that is to use a market model (CAPM or another factor model based on its deviations) instead of a constant mean return model. This is actually very close to the original idea of a synthetic control. The synthetic control (the counterfactual or normal return model) is also a factor model. Therefore, we can define as in Abadie, et al. (2010) a factor model for the dynamics of the latent process $R_{i,t}^N$, that is the return that would be observed for security i if the volatility auction had not taken place at time T_0 . In finance it is not difficult to come up with a generally accepted factor model, for example in traditional event studies that factor model is the CAPM.

$$AR_{1,t} = R_{1,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t} \quad (3.8)$$

where $R_{m,t}$ denotes the market return. We can go a step further and propose a hybrid approach where abnormal returns are defined as the difference between the observed returns of the asset and the returns of the synthetic portfolio. However, such returns can also be conditioned on the market return

$$\hat{\alpha}_{1,t} := AR_{1,t} = R_{1,t} - \sum_{j=2}^J w_j^* \hat{R}_{j,t}, t \in (T_0, T] \quad (3.9)$$

$$\hat{R}_{j,t} = \hat{\alpha}_j - \hat{\beta}_j R_{m,t}, t \in [1, T_0) \quad (3.10)$$

There is however a problem with this approach in stock markets composed of thinly-traded securities. In these markets the market index might give an important weight to the asset we are trying to analyze and therefore this conditioning method will not provide a proper counterfactual.

Chapter 4

Empirical analysis

For a proper selection of the sample for implementing SMC and calculating the abnormal returns, we selected each of the eighth assets and introduced the next criterias for a given asset A_i $i = 1, \dots, 8$:

1. We identified the time and day of the volatility auction of A_i .
2. Discarded sucesive volatility auction.
3. Checked that the volatility auction was not triggered at the begining nor the ending of the trading session.
4. Verified that the asset A_i had trading activity during the day.
5. Excluded the assets $A_{j \neq i}$ that during the day had an activation of a volatility auction. Also if the assets $A_{j \neq i}$ did not have trading activity either before or after the auction of A_i .
6. Extracted the series for the time before and after the auction of A_i .

Even after these selection criterias, we had to exclude some assets $A_{j \neq i}$ that belonged to the A_i syntetic portfolio, and some auctions due to the asynchronicity of information for computing returns, and volatility. Finally for a given asset A_i we calculated the optimal weigths for each $A_{j \neq i}$ that replicated the returns of A_i , and the abnormal returns.

4.1 Result

For PFBCOLOM, PREC, ECOPEL and ISA a single auction was selected, in tables 4 to 7 we report the optimal weigths and the assets that replicated the abnormal returns

before and after the auction, some weights are negative indicating that in order to replicate the asset the portfolio must contain short sales.

In figures 5.4 to 5.7, we report the real returns vs. the returns of the tracking portfolio. For PFBCOLOM, ECOPETL and ISA the adjustment of the return series before the auction is quite similar, on the other side PREC adjustment is not as precise. This behaviour is verified in figures 5.8 to 5.11 where the abnormal returns for PREC show notorious differences before the auction is triggered.

In table 5.6 we report the results for the Cumulative Abnormal Returns and the cumulative returns of the asset affected by the volatility call auction. In the framework of Synthetic Control Methods, the cumulative abnormal returns indicate the overreaction or underreaction of the affected variable. We find an underreaction for PFBCOLOM, while the other assets overreact after the auction. The magnitude of the reaction is observed in the cumulative returns, where we can conclude that for PFBCOLOM, ISA, and ECOPETL there is a change in the trend of returns when the auction is set in place.

In table 5.7 are the calculations of realized volatility for PFBCOLOM before the auction are almost identical for the synthetic portfolio and the observed series, the result contrast with the realized volatility after the auction. In this case, the observed realized volatility was higher than the synthetic asset volatility. Nevertheless the results for the other assets are quite heterogeneous, realized volatility calculations before the auction appears to differ in the synthetic portfolio and observed returns series. Therefore different robustness test should be applied to verify if the calculated weights provide a proper adjustment, this could be done by checking if the difference between the observed returns and the synthetic portfolio returns are statistically significant.

Chapter 5

Conclusions

In this paper we exposed the difficulty of measuring the effects of a volatility call auction due to the lack of a proper counterfactual, in the literature some methodologies as pseudo-events or comparisons between assets with familiar characteristics have been used.

We suggest a different methodological approach by proposing synthetic portfolio for event studies, this approach could allow us to build a counterfactual. Our counterfactual is a weighted average portfolio of the returns of assets, which have not been affected by the volatility call auction during the period of time when the mechanism was triggered for a given security.

We find that for Colombian Stock Market securities, the asynchronicity of intraday data reduces the analysis to a selected group of stocks, nevertheless it is possible to find weights that could provide an accurate synthetic portfolio that replicates the returns of a security affected by a volatility auction. For the assets we study the realized volatility increases after the auction, indicating that the mechanism is not enhancing the price discovery process by reducing volatility.

In future research we plan to design or implement different tests in order to verify the statistical significance of our results for Cumulative Abnormal Returns. These tests will provide a better inference about the volatility of assets before and after the auction.

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FIGURE 5.1: Volatility auction mechanism

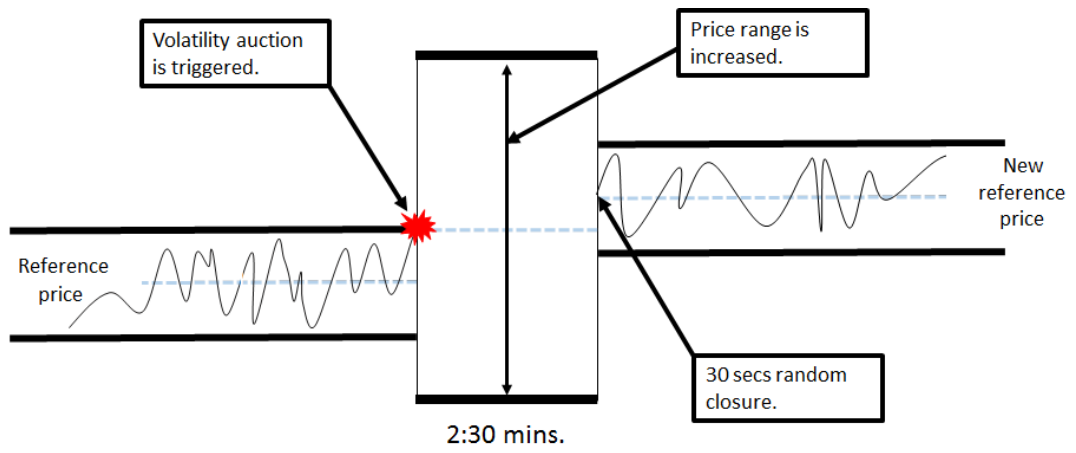


FIGURE 5.2: Synthetic Control Method

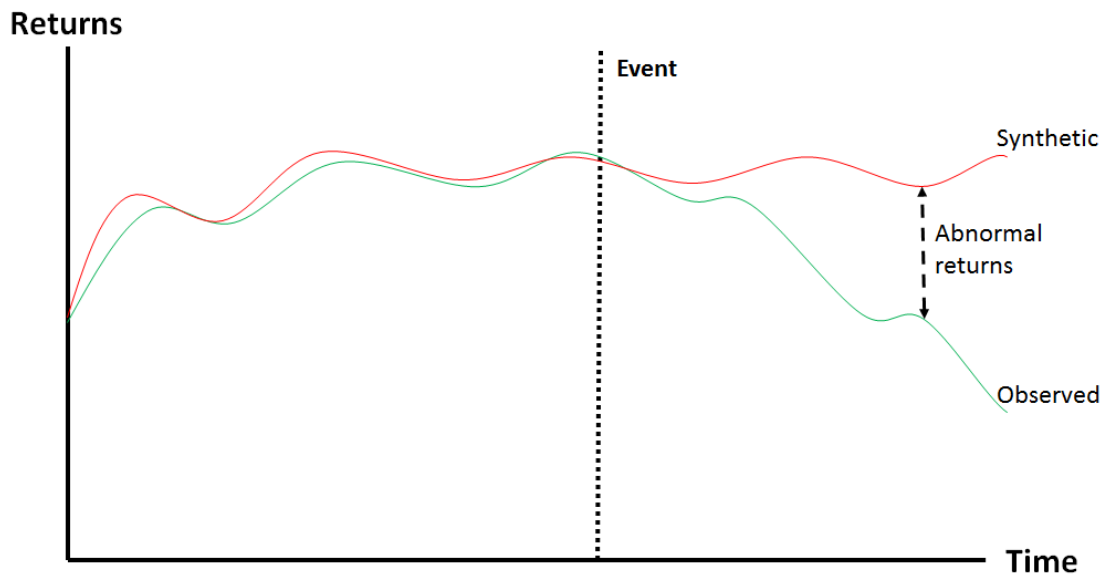


FIGURE 5.3: Histogram of auctions

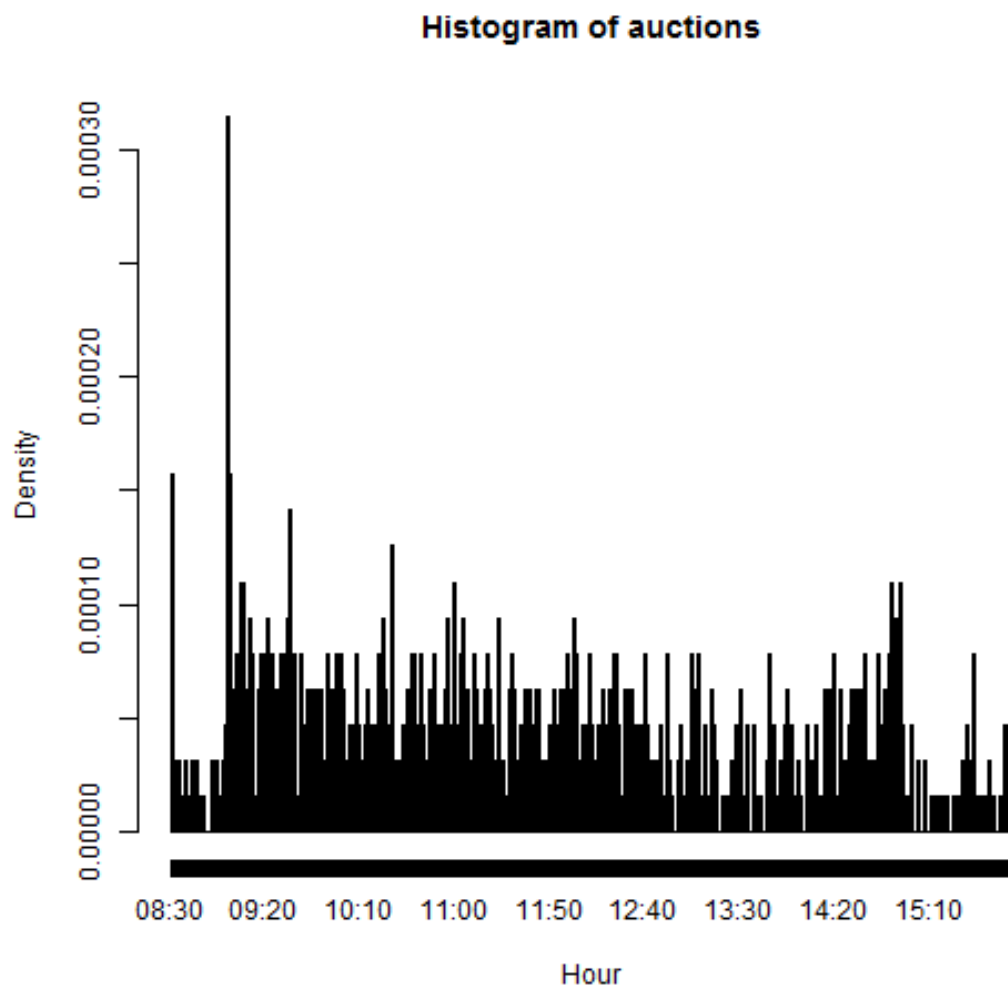


FIGURE 5.4: PFBCOLOM returns.

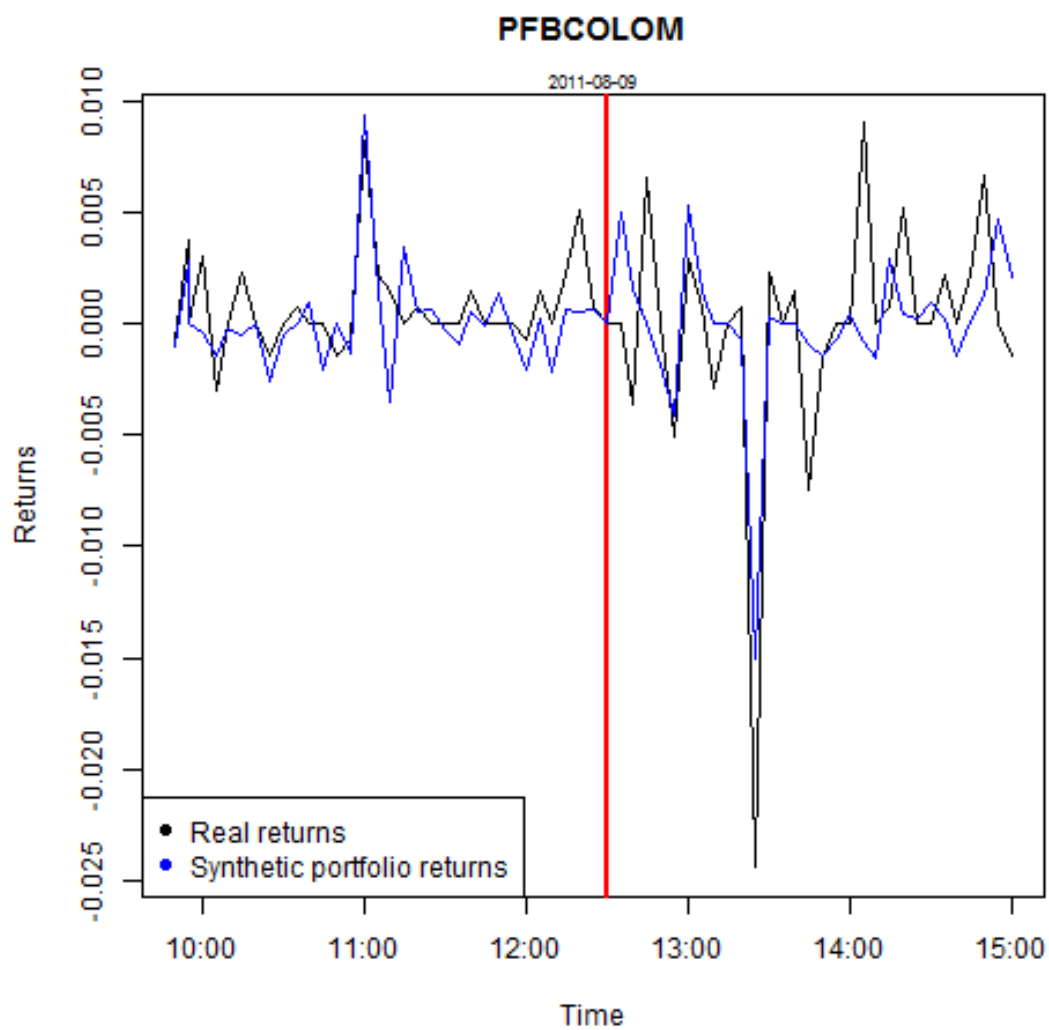


FIGURE 5.5: PREC returns.

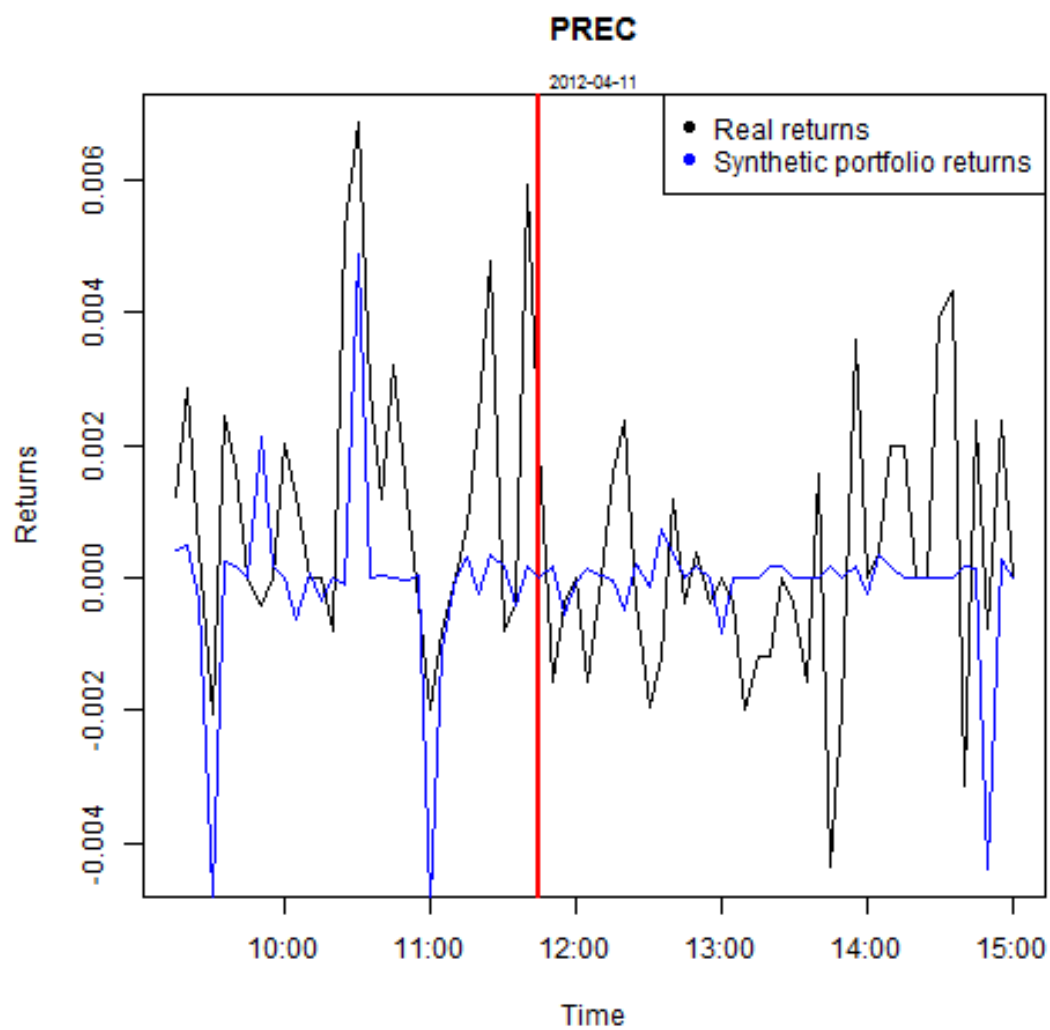


FIGURE 5.6: ECOPETL returns.

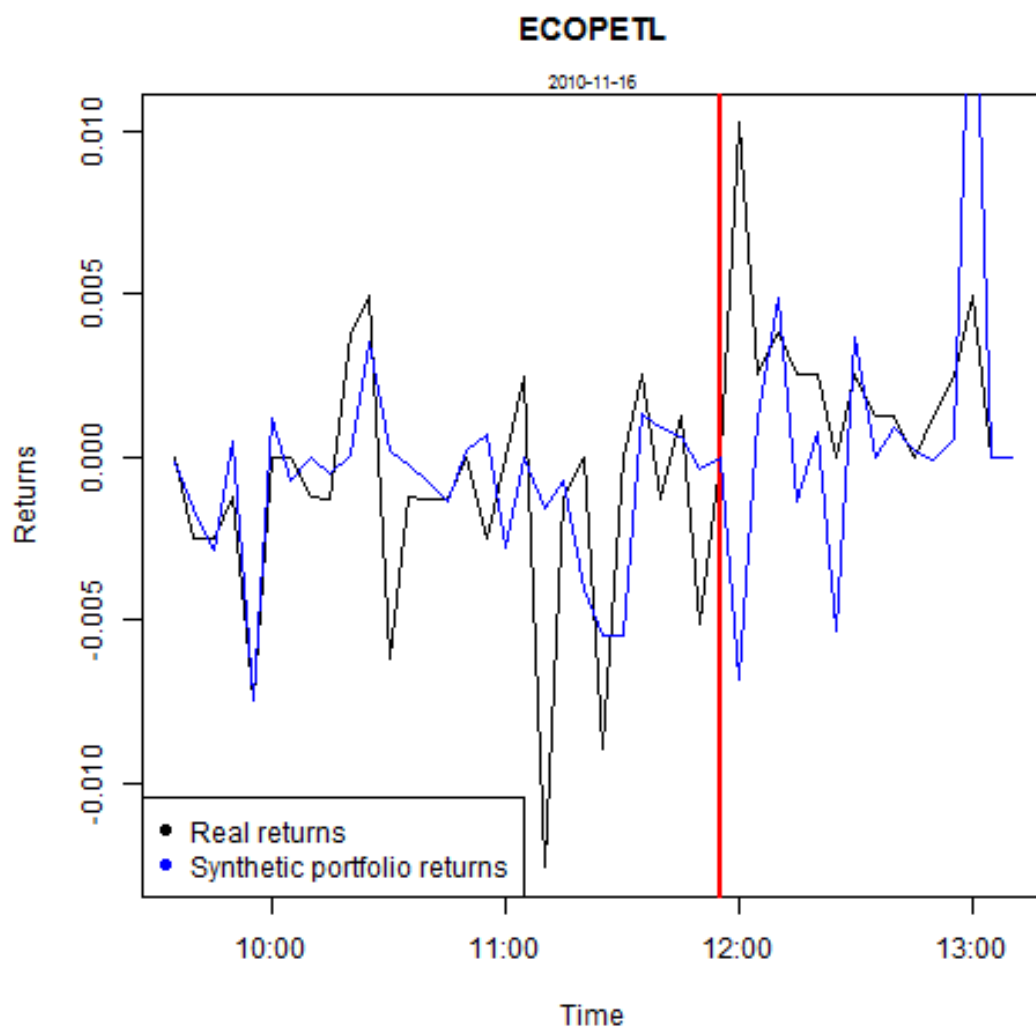


FIGURE 5.7: ISA returns.

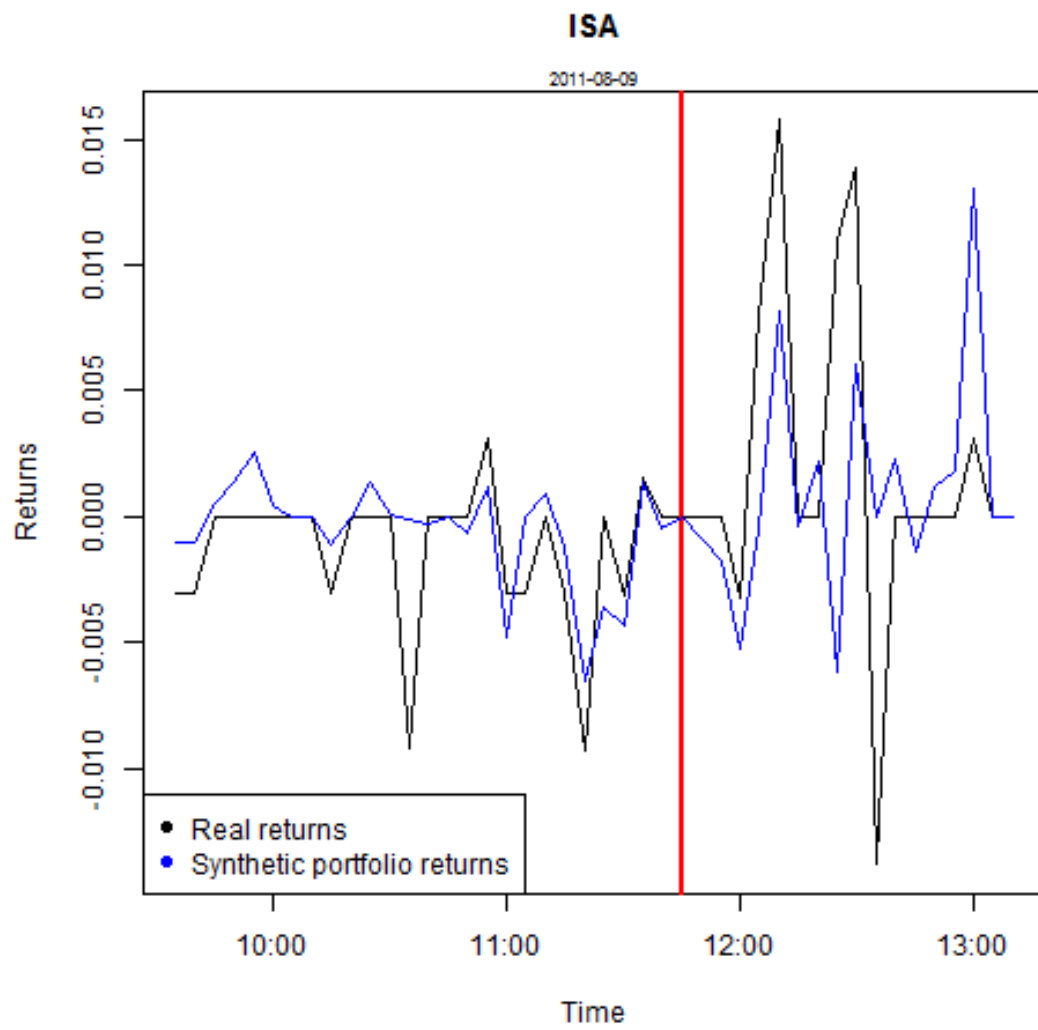


FIGURE 5.8: PFBCOLOM abnormal returns.

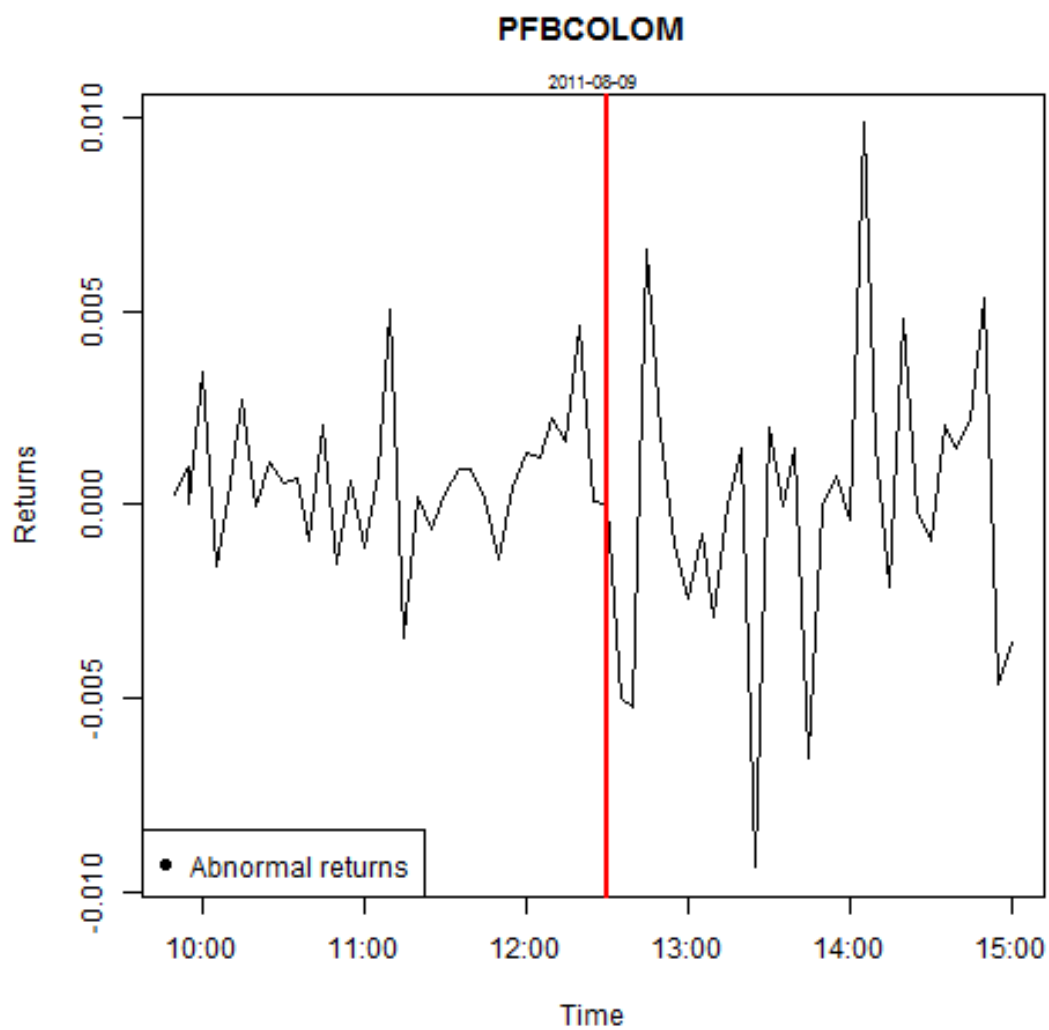


FIGURE 5.9: PREC abnormal returns.

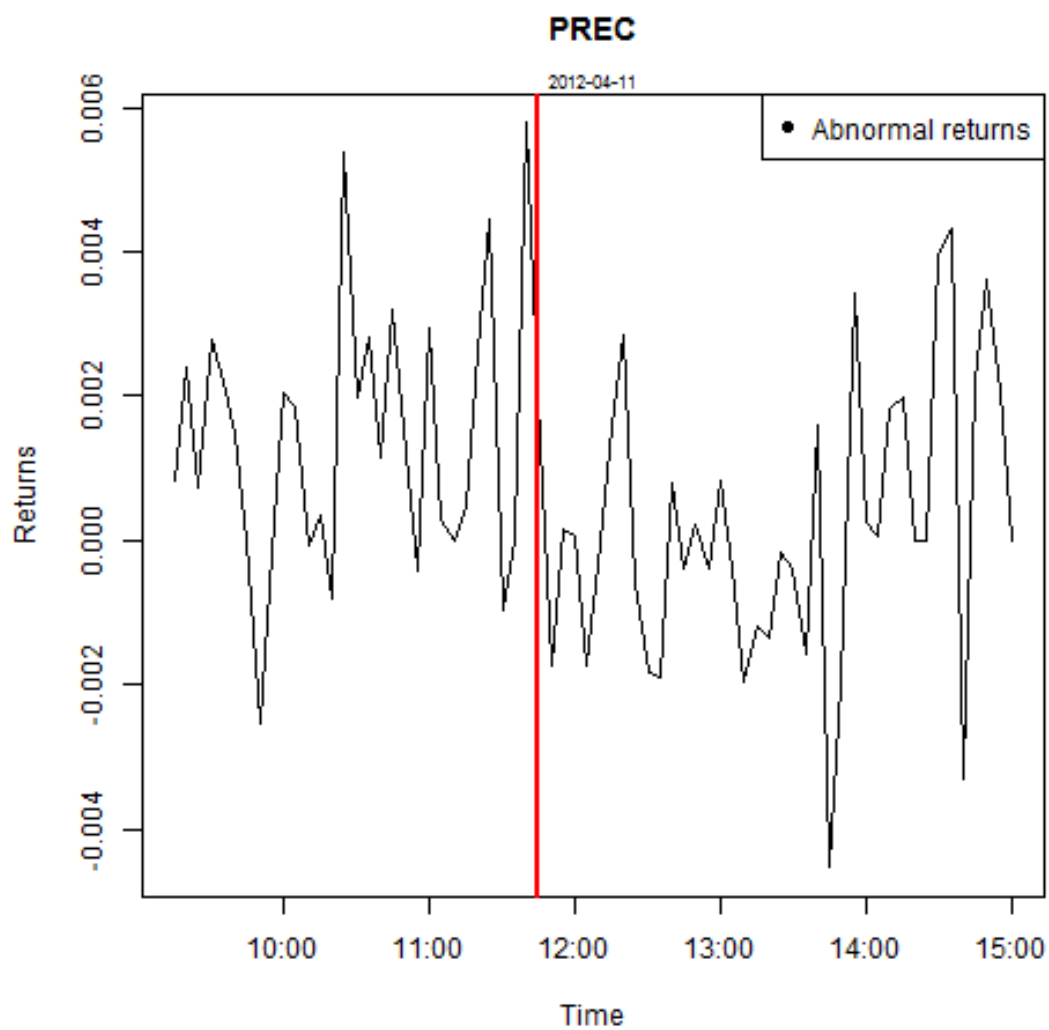


FIGURE 5.10: ECOPETL abnormal returns.

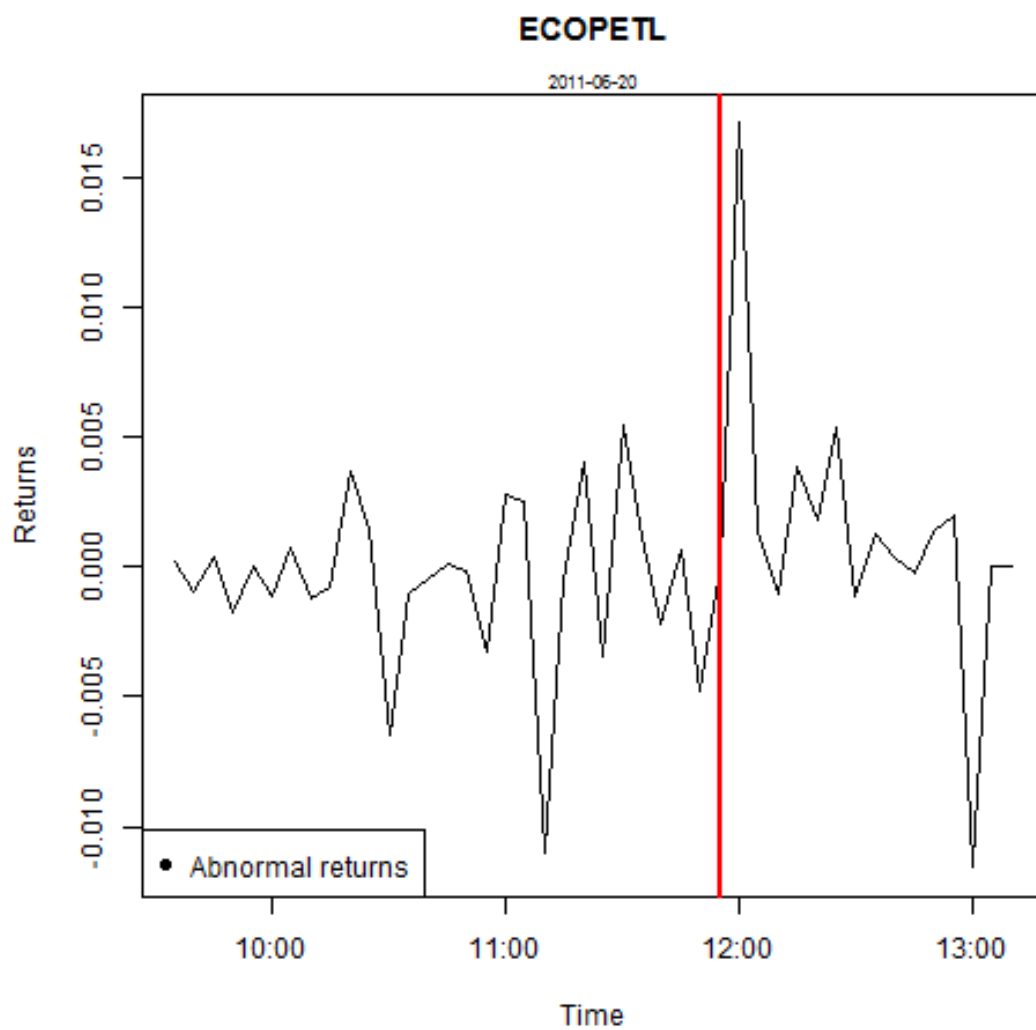
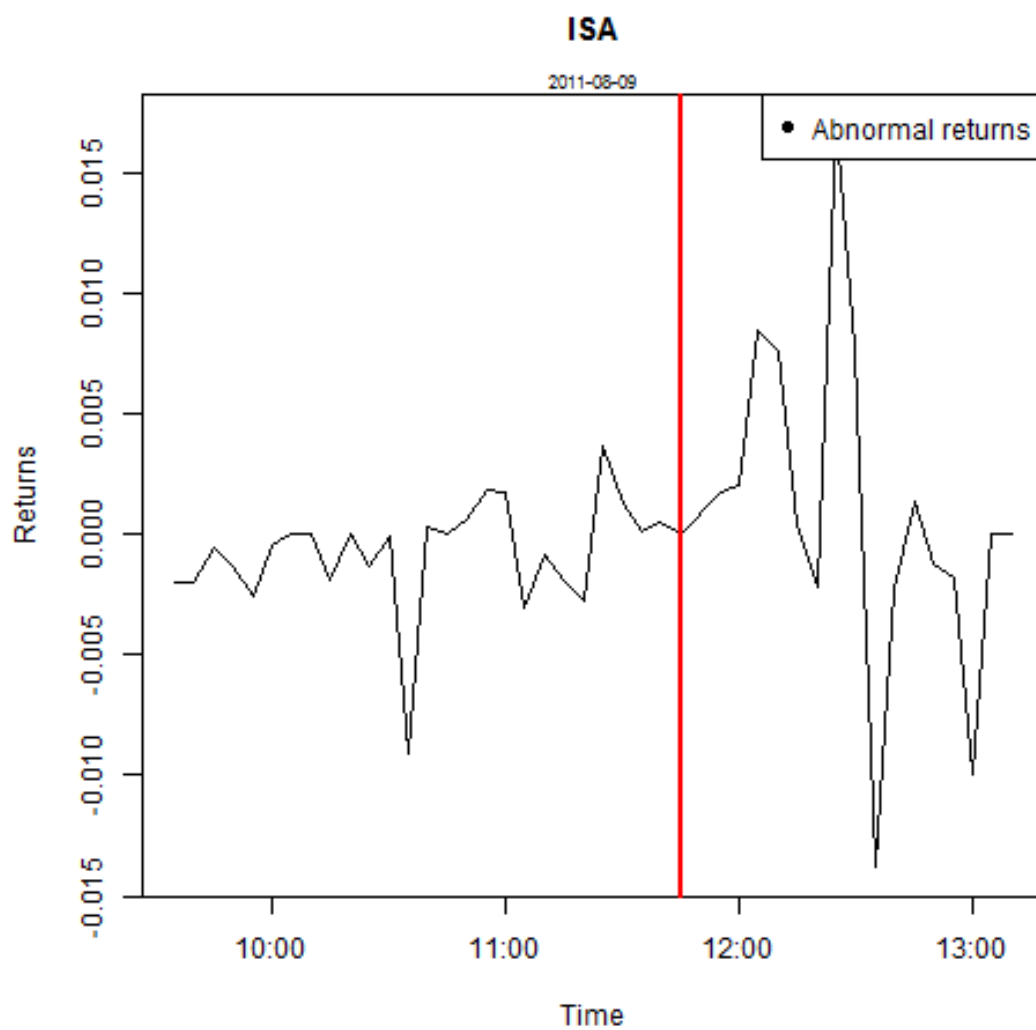


FIGURE 5.11: ISA abnormal returns.



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TABLE 5.1: Numbers of auctions per asset

<i>Nemo</i>	<i>Number of auctions</i>	<i>Percentage</i>	<i>Nemo</i>	<i>Number of auctions</i>	<i>Percentage</i>
<i>BMC</i>	239	22.5	<i>PFCORCOL</i>	7	0.66
<i>VALBAVA</i>	157	14.78	<i>NUTRESA</i>	6	0.56
<i>COLTEJ</i>	92	8.66	<i>INVARGOS</i>	5	0.47
<i>CNEC</i>	78	7.34	<i>PFDVVND</i>	5	0.47
<i>ENKA</i>	73	6.87	<i>BCOLO</i>	4	0.38
<i>CONCONC</i>	41	3.86	<i>BOGOTA</i>	4	0.38
<i>PFBHEMB</i>	35	3.3	<i>EEB</i>	4	0.38
<i>PREC</i>	33	3.11	<i>GRUPOSUR</i>	4	0.38
<i>ETB</i>	30	2.82	<i>ECOPETL</i>	3	0.28
<i>MINEROS</i>	30	2.82	<i>PFBCOLO</i>	3	0.28
<i>ODINSA</i>	30	2.82	<i>ISA</i>	2	0.19
<i>TABLEMA</i>	25	2.35	<i>PAZRIO</i>	1	0.09
<i>FABRI</i>	19	1.79	<i>BBVACOL</i>	0	0
<i>BIOMAX</i>	18	1.69	<i>CARTON</i>	0	0
<i>CELSIA</i>	16	1.51	<i>GASNAT</i>	0	0
<i>EXITO</i>	16	1.51	<i>IMUSA</i>	0	0
<i>AVAL</i>	15	1.41	<i>OCCID</i>	0	0
<i>BVC</i>	15	1.41	<i>POPULA</i>	0	0
<i>ISAGEN</i>	13	1.22	<i>PROMIG</i>	0	0
<i>SIE</i>	12	1.13	<i>PROTECC</i>	0	0
<i>CEMARGOS</i>	10	0.94	<i>SANTAN</i>	0	0
<i>CORFICOL</i>	9	0.85	<i>SOCBOL</i>	0	0
<i>INTBOL</i>	8	0.75			

TABLE 5.2: PFBCOLOM Synthetic portfolio composition

<i>GRUPOSUR</i> 0.3966	<i>CONCONC</i> 0.3647	<i>AVAL</i> 0.1775	<i>INVARGOS</i> 0.1474	<i>ETB</i> 0.0918
<i>CEMARGOS</i> 0.0871	<i>PFDVVND</i> 0.0235	<i>BCOLO</i> 0.0192	<i>INTBOL</i> 0.0107	<i>PREC</i> 0.0011
<i>SIE</i> −0.011	<i>ECOPETL</i> −0.016	<i>CNEC</i> −0.078	<i>NUTRESA</i> −0.106	<i>FABRI</i> −0.108

TABLE 5.3: PREC Synthetic portfolio composition

<i>FABRI</i> 0.8411	<i>AVAL</i> 0.5320	<i>EXITO</i> 0.0670	<i>PFDVVND</i> 0.0120	<i>CORFICOL</i> −0.0773
<i>ISA</i> −0.0886	<i>ECOPETL</i> −0.0908	<i>EEB</i> −0.1953		

TABLE 5.4: ISA Synthetic portfolio composition

<i>CEMARGOS</i> 0.6789	<i>INTBOL</i> 0.6101	<i>ETB</i> 0.1146	<i>TABLEMA</i> −0.0599	<i>GRUPOSUR</i> −0.1664
<i>EEB</i> −0.1773				

TABLE 5.5: ECOPETL Synthetic portfolio composition

<i>INTBOL</i> 0.9213	<i>CEMARGOS</i> 0.4100	<i>EEB</i> 0.3169	<i>ETB</i> 0.0413	<i>FABRI</i> 0.0378
<i>TABLEMA</i> −0.2821	<i>GRUPOSUR</i> −0.4452			

TABLE 5.6: Returns results

Asset	Cumulative Abnormal Returns		Cumulative Returns	
	Before	After	Before	After
PFBCOLOM	2.1654%	−0.4022%	2.5131%	−0.5857%
PREC	4.4041%	0.6338%	4.0658%	0.3145%
ISA	−1.9793%	1.5131%	−3.5253%	3.4486%
ECOPETL	−1.5981%	2.0370%	−4.2666%	3.5447%

TABLE 5.7: Volatility results

Asset	Realized Volatility			
	Observed		Synthetic	
	Before	After	Before	After
PFBCOLOM	0.0153%	0.0928%	0.0152%	0.0331%
PREC	0.0202%	0.0130%	0.0079%	0.0022%
ISA	0.0239%	0.0831%	0.0118%	0.0355%
ECOPETL	0.0442%	0.0076%	0.0174%	0.0345%

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