Pontifícia Universidade Católica
do Rio de Janeiro

Francisco Eduardo de Luna e Almeida Santos

Essays on market microstructure and financial econometrics

Tese de Doutorado

Thesis presented to the Postgraduate Program in Economics of the Departamento de Economia,PUC-Rio as partial fulfillment for the degree of Doutor em Economia.

Advisor: Prof. Márcio Gomes Pinto Garcia
Co-advisor: Prof. Marcelo Cunha Medeiros

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Resumo

Francisco Eduardo de Luna e Almeida Santos; Garcia, Márcio Gomes Pinto (orientador); Medeiros, Marcelo Cunha(co-orientador). **Ensaios em microestrutura de mercado e econometria de finanças.** Rio de Janeiro, 2013. 111p. Tese de Doutorado - Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

A tese consiste em três artigos relacionados à literatura de microestrutura de mercado e econometria de finanças. No primeiro artigo, a relação entre fundamentos macroeconômicos e preços de ativos é explorada por meio da estimação do impacto de anúncios macroeconômicos no mercado futuro brasileiro. Para tal fim, a literatura de estudo de eventos combinada à disponibilidade de dados intradiários oferece uma abordagem adequada ao tema em questão. Usando dados entre Outubro de 2008 e Janeiro de 2011, encontramos que os anúncios macroeconômicos externos dominam a mudança de preços nos mercados futuros de câmbio e ações, enquanto que o impacto dos anúncios domésticos é restrito aos contratos de juros futuros. O estudo também fornece evidências de que a reação em termos de preços é condicional ao estado da economia e também documentamos o impacto em volume e spreads. No segundo artigo, estudamos a descoberta de preços (ou price discovery) no mercado de câmbio brasileiro e determinamos em qual dos mercados (à vista ou futuro) o ajuste de preços é mais rápido à chegada de novas informações. Nossos resultados apontam que o mercado futuro domina a descoberta de preços, sendo responsável por 66,2% da variação no choque do preço fundamental e por 97,4% da composição do preço fundamental. Numa perspectiva dinâmica, o mercado futuro é também o mais eficiente uma vez que, quando ambos os mercados estão sujeitos a choques no preço fundamental, o mercado futuro é aquele que retorna mais rapidamente ao equilíbrio. No terceiro artigo, um modelo de variância-covariância realizada é proposto utilizando uma carteira composta pelas ações mais líquidas do índice Ibovespa. O objetivo é avaliar os ganhos econômicos obtidos quando o investidor segue uma

estratégia de volatility timing, baseada em diferentes modelos de previsão para a matriz de covariância condicional. Comparando com os modelos tradicionais de volatilidade, os resultados mostram que os ganhos econômicos associados ao uso de medidas de covariância realizada são positivos quando o risco de estimação é controlado, crescendo a medida que aumentamos os retornos-alvo da carteira.

Palavras-chave

Anúncios; descoberta de preços; covariância realizada; dados em alta frequência

Abstract

Francisco Eduardo de Luna e Almeida Santos; Garcia, Márcio Gomes Pinto (advisor); Medeiros, Marcelo Cunha(co-advisor). **Essays on market microstructure and financial econometrics.** Rio de Janeiro, 2013. 111p. Doctoral Thesis - Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

The thesis comprises three articles related to market microstructure and financial econometrics. In the first article, the relationship between macroeconomic fundamentals and asset prices is explored by estimating the impact of macroeconomic announcements in the Brazilian futures market. In order to achieve this objective, the event study literature combined with the availability of intraday data offers a suitable approach. Using data from October 2008 to January 2011, we find that external macroeconomic announcements dominate price changes in the Foreign Exchange and Ibovespa futures markets, while the impact of the domestic ones is mainly restricted to Interest Rate futures contracts. We also provide evidence that price reactions are conditional on the state of the economy and document the impact on volume and bid-ask spreads. In the second article, we study price discovery in the Foreign Exchange market in Brazil and indicate which market (spot or futures) adjusts more quickly to the arrival of new information. We find that futures market dominates price discovery since it responds for 66.2% of the variation in the fundamental price shock and for 97.4% of the fundamental price composition. In a dynamic perspective, the futures market is also more efficient since, when markets are subjected to a shock in the fundamental price, it is faster to recover to equilibrium. In the third article, a model of realized variance-covariance is proposed using a portfolio with the most liquid stock assets of Ibovespa. The purpose is to evaluate the economic gains associated with following a volatility timing strategy based on the model's conditional forecasts. Comparing with traditional volatility methods, we find that economic gains associated with realized measures perform well when estimation risk is controlled and increase proportionally to the target return.

Keywords

Announcements; price discovery; realized covariance; high frequency data

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1The impact of economic announcements in the Brazilian futures market

1.1.Introduction

The study of the behavior of asset returns is central for financial economists and a wide range of applications benefit from such interest, including risk management, market efficiency and asset pricing. It is far from clear how markets arrive at prices and, more specifically, how they incorporate news related to the state of the economy. In this sense, we want to explore the controversy over the relationship between macroeconomic fundamentals and asset price formation by estimating the impact of economic announcements in the Brazilian futures market. Previous studies have found it difficult to measure such effects, not only due to identification issues but also to data quality. The event study literature combined with the availability of intraday data offers a suitable approach to identify exogenous shocks, overcoming some difficulties inherent to the literature. Conversely, it brings econometric issues related to transaction microstructure that needs to be addressed.

We contribute to the existent literature by incorporating liquidity (trading volume) and informational (bid-ask spread) variables as opposed to the prevailing focus on prices and returns. We believe that market participants will benefit from a broader outlook of time periods surrounding macroeconomic announcements as there are a number of reasons why we should give importance to evaluate its impact on the financial market. At first place, it provides information on the timing of market interventions. We will investigate, for instance, return and liquidity parameters for different assets traded at the futures market nearby an interest decision from the Federal Committee of Open Market (FOMC). The Central Bank of Brazil (CBB), as a regular participant in the market, could benefit from this valuable information in the process of deciding whether or not intervene in such instances. Since investors form expectations prior to scheduled announcements, understanding the overall market reaction may help them rebalance portfolios after its release. Also, investors take into account broad market conditions in their decision to operate, not only prices. Informed agents, for instance, may prefer conditions that favor anonymity in order to hide its private information. In such a case, anticipating situations of decreasing or increasing volumes may support the choice for post-announcement operations.

In a highly integrated and electronic-based market, events that convey price information should be readily incorporated into prices. This is especially true in such a liquid market as the Brazilian futures one, where the presence of High Frequency Trading (HFT) is widely acknowledged. With that in mind, we compute the aggregate announcement effect by summing up the coefficient estimates of the regression analysis over progressive larger time windows. This procedure enables us to offer different dimensions on market´s reaction. For instance, we give an indication of how fast markets react to each announcement type, enabling us to discuss its relative efficiency. Persistence is another parameter to look carefully, since some news may impose only transitory effects on prices. But to what extent does it translate into movements in the financial market? Our third metric, the impact intensity on each market, should answer this question. Combined, they give support to investment strategies definition, an additional motivation for this work.

Finally, the event study literature concentrated its efforts in understanding market reactions and co-movements in central economies. In this sense, it will be particularly interesting to compare the results applied to an emerging market, in particular the Brazilian one, in which external factors supposedly exert great influence on the development path of the domestic economy. Andritzky et al (2007,2011), for instance, already studied first and second order effects of macroeconomic announcements for the most liquid emerging market bonds.

Note, however, that both studies were restricted to the sovereign bond market as opposed to our study that focuses on the main domestic markets of an emerging country.

The transactions' data is provided by BM&FBovespa (BVMF), the Brazilian company responsible for clearing and trading futures and equity market transactions. The sample period starts at October 2008 until January 2011, totaling 513 days, and contains tick-by-tick information from the interest rate (IR), foreign exchange (FX) and stock index (Ibovespa) futures markets on prices, volume and bid and ask offers as well. In addition, we construct an announcement database with the surprise component of six economic indicators. The domestic announcements are the interest rate decision made by the monetary policy committee (COPOM), the monthly industrial sector production (PIM) and the consumer inflation (IPCA) while their external counterparts, all of them originated in the US, are the FOMC interest rate decision[1], non-farm payroll indicator (PR) and the consumer price one (CPI).

The main findings are as follows. First, our study provides evidence of the link between economic fundamentals and asset prices. We find that external macroeconomic announcements dominate price changes in the FX and Ibovespa futures markets where reactions are, in general, immediate and persistent relative to monetary (FOMC) and real economy (PR) surprises. We also conclude that the IR market is affected by events that potentially affect its monetary rule, based on the inflation targeting approach. This is the reason why the impact of announcements in the IR market is less intense and restricted to domestic events. State dependency, in turn, can interfere in the relative magnitude of the coefficients that measure the impact of announcements, occasionally cancelling out predicted impacts as shown by the estimates for the IPCA announcement.

In the IR market, we find an excess return of -0.107 p.p. in response to a 25 basis points' COPOM surprise and 0.041 p.p. in response to a 0.10 p.p. IPCA surprise. Both impacts are persistent only up to ten minutes after each release and holds in the expansion period. In the FX and Ibovespa futures markets, two features emerge. First, we conclude that the impact of each announcement, when significant, is more persistent, eventually reaching twenty minutes after its public release. Also, we find evidence that external events dominate both markets. Take the example of the FX market, where external monetary policy is the main factor driving returns where a 25 basis points' FOMC surprise raises FX returns in 0.191 p.p. and 0.089 p.p. in the full sample and expansion period, respectively, twenty minutes after its release. Ibovespa futures' analysis reveal an additional and important feature, related to the link between fundamentals and asset prices: reactions are more persistent and spread among all announcements, except for inflation-related ones. A COPOM surprise, for instance, amounting to 25 p.b., raise Ibovespa futures returns by 0.094 p.p. in the expansion period estimates, twenty minutes after its release. Also, a US monetary policy easing is related to positive stock returns in Brazil. Instead, non-farm payroll records are positively associated with domestic stock index returns suggesting that the dividend effect is higher than the cost of capital one and also that real economy shocks are correlated between Brazilian and US economies.

Actually, an investment strategy based on the conditional price reaction of each market showed promising results in an out-of-sample study. Under this approach, investors decide its trading position depending on the combination between sign impact and surprise direction. Actually, it presents promising results in an out-of-sample study since we are able to correctly identify returns' signals, conditional on the surprise's signal, in 70% of the cases. Besides, aggregate results show positive returns for all markets.

Finally, we assess trading volume impact and conclude that, contrary to price reaction, they are widespread among all announcements and business cycles. We also document large differences in the relative magnitude of trading volume reactions that theory attributes to each announcement's precision. The significant reaction from the IR market with respect to COPOM announcements and from FX and Ibovespa markets relative to FOMC and PR ones is an indication of differential levels of informational content. We find that bid-ask spreads often revert in face of external announcements what can be attributed to different trading phases.

[1] We also included Quantitative Easing (QE) announcements.

In Section 1.2, we briefly present the main references on this subject, focusing on the recent developments in event studies. Section 1.3 explore the database and give details of its construction. Next, we present the methodology used in the paper, which will be based on the work of Andersen et al (2007) and discuss the results in Section 1.5 with an application to the real data. Finally, our concluding remarks are offered in Section 1.6.

1.2.Related work

The link between economic fundamentals and asset prices has been extensively studied in the financial economic literature. When working with daily data, the biggest issue is to identify structural shocks. An identification strategy based on the data heteroskedasticity is proposed by Ehrmann et al (2011) in a daily frequency study. The authors defined different variance regimes and assumed that some parameters were stable across them. Besides, some signal restrictions were employed to guarantee identification. This framework was used to identify the degree and direction of financial transmission between Euro area and the United Stated in the bond, stocks and exchange rate markets. The authors found that, although the causality runs in both directions, the US market had a higher impact. A similar approach has been applied by Rigobon & Sack (2003) in their study on the contemporaneous impact of stock and bond markets.

The use of high frequency data makes it possible to identify a structural shock by focusing on specific situations when a prevailing force moves the financial market. In the high frequency event study literature, the central hypothesis is that announcements have price relevant information that is quickly incorporated to prices through trading.

The high frequency association between returns and fundamentals has been acknowledged by Fleming & Remonela (1997). Using data from August 1993 to August 1994, the authors documented that the 25 largest price moves and trading surges in the US bond market were related to macroeconomic announcements. Fair (2003) also took advantage of the availability of intraday data and identified abnormal returns on the US stock market from 1982 to 1999. Such returns were, then, associated with economic news released at exactly the same time. Moreover, the author corroborated that each market was moving according to what is expected from theory, depending on the announcement type studied.

On the same agenda, Faust et al (2007) evaluated the effect of macroeconomic announcements on the bond and exchange rate markets. Contrary to Fair (2003), the authors made a regression-type analysis where the dependent variable was the return on a 20-min window around each announcement and the independent one was its surprise component. In general, the authors found that stronger-than-expected releases[2] for real and nominal activity cause dollar appreciation and raise U.S. rates at all horizons.

Also based on a high frequency event-study analysis, Andersen et al (2003) proposed an alternative structure on the construction of the database of returns which will be explored more deeply in Sections 1.3 and 1.4. In short, each 5-min return is kept as a separate observation around a 100-minute window around announcements. The explanatory variable is the surprise component of each announcement that is put in place in synchrony with the exact time of its release. Using 5-min returns from January 1992 to December 1998, the authors analyzed the impact of macroeconomic announcements on the relationship between the dollar and major currencies (German Mark, Japanese Yen, British Pound, Swiss Franc and Euro), finding that that bad news have greater impact than good ones, the so-called asymmetric effect. Departing from the same framework, Andersen et al (2007) concluded for the existence of a state-dependent link from economic fundamentals to the bond, exchange and stock market in US, German and British markets. The authors also found that systematic effects are usually short-lived and restricted to the first 5-min interval.

Recent high frequency studies provided additional evidence of the link between economic fundamental and asset prices in different markets and sample periods. Using 5-min returns from

[2] . Inflation surprises (CPI and PPI) were not significant to exchange rate returns at the 1% level.

September 2000 to September 2008, Hussain (2011) documented the significant influence of domestic monetary policy on the return and volatility of US and four European stocks (Germany, France, Switzerland and UK). Lapp & Pearce (2012), in turn, found that greater than expected inflation and employment rise futures bond prices. Beechey & Wright (2009) also confirmed the highly significant and immediate impact of macroeconomic announcements on long term US bonds and inflation-nominated ones between February 2004 and June 2008.

Rosa (2011) made the important distinction between policy decisions and statements in their study on the relationship between the US FX market and monetary announcements. Estimation results showed that both types of monetary announcements have economically large and highly significant effects on the FX market. Contrary to Andersen et al (2007), though, it shows that the impact of FOMC surprises takes more time to be absorbed, lasting between 30 and 40 minutes. Conrad & Lamla (2010) created communication indicators to deal with the issue of interpreting monetary statements in their analysis of first and second order effects of the European Central Bank (ECB) communications in the EUR-USD exchange rate. Due to the long memory property of the volatility, the option for a FIGARCH approach provided a good fit. The communication indicators were, then, used as explanatory variables in the FIGARCH model, providing the main conclusion of the article that price and risk paths are affected by monetary communications.

Melvin & Ahn (2007) adopted a different strategy for the estimation of the impact of FOMC days on the German Mark and Dollar between 1994 and 1995. Using 5-min returns, the authors identified regime switches around ten FOMC meetings and associated them with informed or liquidity trading. They concluded that the switch to informed trading occurs during the meeting, suggesting an earlier adjustment of positions prior to its end.

1.3.Database construction

The futures market in Brazil is concentrated at BVMF, the company that manages domestic derivatives transactions. We collected data from specific interest rate, stock index and exchange futures contracts from 1st October 2008 until 31st January 2011, or 513 days[3]. As any intraday database, it contains price, volume, quantity, date and time for every operation (closed deals, bid and ask offers).

Before getting into the details of the database construction, it is important to discuss the reason why did we opt for the futures market instead of the spot one. When it comes to interest rates, the secondary spot market is highly illiquid and does not provide a good price reference. When the Central Bank of Brazil performs auctions on federal bonds, for instance, the decision on which offers to accept are based on the nearest to maturity futures contract. The spot FX market, in turn, is approximately nine times smaller than the futures one since many operations that should be done in the spot market are performed in the futures market due to regulatory restrictions. Finally, at the sample period, BVMF released a product[4] whose reference is the Brazilian stock index, Ibovespa. However, its liquidity cannot be compared to that of Ibovespa futures contracts.

1.3.1.Returns, trading volumes and spreads

In each market, there are contracts with different maturities traded at the same day. In the FX market, in particular, expiration date is in the first business day of the contract month. The shorter term ones, expiring in the subsequent month, are always the most liquid ones, concentrating approximately 90% of the FX trading volume. Two days before expiring, traders move to following contract month and the final database was selected by switching contracts according to liquidity. Ibovespa futures[5] market are similar to FX ones, where short term

[3] There are 64 random missing days in our data.
[4] PIBB is an Exchange Traded Fund (ETF) that references Ibovespa and can be traded as a stock at BVMF.
[5] BM&F Bovespa codes have six digits. The first three identify the contract ("IND", for Ibovespa futures, "DOL", for exchange rate ones and "DI1" for interest rates). The final three digits identify month and year of contract maturity.

contracts concentrate most of the trading volume and, every two months, there is a switch to the nearest to maturity contract two days before expiring.

Although liquidity remained a choice criterion, the fact that the IR futures market works in a different way brings an additional element to its database construction. In a given trading day, there is a wider range of IR contract maturities with high trading volume, including medium and long term contracts. This feature implies a tradeoff between liquidity and risk premium since we must minimize large differences in risk premium as we switch between contracts. Given that that January contracts are the most traded ones, between October 2008 and December 2008, the selected contract is the one expiring in January 2010. In 2009 and 2010, the selected ones expired in January 2011 and January 2012, respectively. Finally, in January 2011, January 2013 contract has been the selected one. Such procedure leads to time to maturity contracts that share a medium term range, between one and two years ahead of the trading day. Since expiration dates are fixed in the IR futures market, differences in time to maturity could be minimized if we expanded the range of contracts used. However, such decision would imply a change in the sampling frequency for all markets, since only January contracts present regular trades compatible with sampling each five minutes.

In terms of number of contracts, IR futures are the most traded ones, followed by FX and Ibovespa. However, when we look at the number of deals, the inverse is true as the FX contracts are the most frequently traded with at least one transaction in each three-second interval, followed by Ibovespa and IR ones which are traded every five and thirty seconds. Note that this is not a homogenous statistic as, nearby announcements, all markets trade more frequently than it does on average. Thus, we do not expect any problems concerning our database, because, as will be demonstrated, we will only work with selected observations around announcement release times.

Table 1: Daily average transaction volumes for each futures market between October 2008 and January 2011

		IR		FX		Ibovespa	
	# days on the database	#of transactions (in thousands)	Volume (in trillion Brazilian reais)	# of transactions (in thousands)	Volume (in trillion US dollars)	# of transactions (in thousands)	Volume (in trillion Brazilian reais)
2008 (October to December)	59	43.2	1.32	551.9	1.94	259.6	0.18
2009	233	164.1	9.30	2,793.4	6.62	1,311.5	0.89
2010	204	161.3	18.8	3,095.6	7.31	2,338.7	1.20
2011 (January)	17	14.7	1.09	169.2	0.46	141.7	0.08

All markets open at 09:00 AM and closes at 06:00 PM. The IR market has a trading interruption between 04;00 PM and 04:50 PM without transactions and we opt to consider that the price remained unchanged throughout this interval. This assumption will not impact our estimates since announcements did not coincide with such interruptions. Since all selected markets are highly liquid, we expect to minimize error measurement by considering the last price in a 5-min grid as the prevailing one. Considering only closed deals, returns for each contract were then computed at each 5-min interval as the log-difference between consecutive 5-min prices. Taking order cancelation into account, spreads are derived as the relative difference between bid and ask values ($\frac{ask-bid}{bid}$) and are measured in percentage points (p.p.). Similarly, the last available spread is the prevailing one at each 5-min grid. Trading volume, in turn, refers to the sum of the number of traded contracts in each 5-min interval.

Table 2 provides information on the sample sizes and summary statistics for the 5-min return, trading volume and spread series. The average returns are, as expected, zero for all

markets with the standard deviation ranging from 0.05% in the FX market to 4.3% in the Ibovespa one. The summary statistics for trading volume also indicate that the FX market is the most liquid one and spread's data have lower levels of dispersion for all markets. All distributions show excess kurtosis and are positively skewed, except the FX market return´s data. Negative first-order autocorrelation holds for all return's distribution. High first-order autocorrelation, as the one observed in the Ibovespa market's trading volume and spread, suggests that persistence is a dominant feature of both distributions.

Table 2: Summary statistics for 5-min returns, trading volumes and spreads

	IR	FX	Ibovespa
Sample size	55,504	55,504	55,504
Final sample	50,274	55,504	55,504
	Returns		
Mean	0.00%	0.00%	0.00%
Standard deviation	0.32%	0.05%	4.05%
Skewness	0.23	-0.13	0.61
Kurtosis	552.2	316.2	1123.4
First-order autocorrelation	-0.30	-0.01	-0.47
	Trading volumes		
	IR	FX	Ibovespa
Mean	973,3	2,586,0	541.9
Standard deviation	2,000.3	2,522.8	411.5
Skewness	5.1	2.7	2.1
Kurtosis	43.9	14.0	8.9
First-order autocorrelation	-0.07	0.51	0.63
	Spreads		
	IR	FX	Ibovespa
Mean	0.11%	0.06%	0.06%
Standard deviation	0.14%	0.08%	0.05%
Skewness	1.8	16.0	6.6
Kurtosis	289.1	553.2	166.6
First-order autocorrelation	-0.15	-0.15	0.64

Note: The table reports sample sizes and summary statistics for returns, trading volume and spreads.

1.3.2. The surprise data

Active traders form expectations over the state of the economy based on the release of macroeconomic indicators. The difference between the observed value and its expectation is called surprise and, according to its direction and intensity, can signal changes in the economy and alter portfolio weights. As our aim is to investigate short-term effects on the futures market, our choice of announcements gave preference to quantitative indicators as opposed to report analysis and policy statements, a kind of release that we would not be able to identify the exact time of the initial impact. In Brazil, it would be the case of the Inflation Report and COPOM minutes[6] whose impact on the domestic term structure of interest rates has been investigated by Janot & El-Jaick (2012). Using daily data and controlling for announcement surprises, the

[6] COPOM minutes (or "Ata do COPOM") are released one week after the target interest rate decision and subjected to deep revision by market participants in order to anticipate the interest rate path.

authors found a significant effect of the first on both the level and volatility of interest rates, but none for the latter. In such circumstance, the construction of communication indicators, as in Conrad & Lamla (2010), would be well suited.

In this sense, we have chosen the most important domestic and external indicators according to the following types of announcement: monetary, price and real economy. Both interest rate decisions made by COPOM and FOMC, respectively, are the most relevant monetary announcements and we included Quantitative Easing (QE) announcements for reasons that will be discussed soon. The choice for the price type is also straightforward as target inflation rules aim at consumer prices. With respect to the real economy, we refer to Fair (2003) to justify the use of non-farm payroll indicator as the author find evidences its superior impact in the US stock market. In Brazil, the domestic industrial production is not only the most reliable one, but is also the subject of many institutional forecasts and attracts the interest of the academy. In Table 3, we present details of the macroeconomic indicators, including its periodicity and additional information concerning the public releases.

Table 3: List of macro indicators, periodicity, time and day of the announcement release

Origin	**Type**	**Indicator**	**Day of the week**	**Periodicity**	**Local Time**	**Brazilian Time**	**Source**	**# events in the sample**
Domestic	Monetary	Interest rate decision (COPOM)	Wednesday	45 days	18:30	18:30	Central Bank of Brazil	15
	Price	Consumer price (IPCA)	Usually on Friday	Monthly|	09:00	09:00	Brazilian Statistical authority (IBGE)	22
	Real Economy	Industrial Production (PIM)	Random	Monthly|	09:00	09:00	Brazilian Statistical authority (IBGE)	26
External	Monetary	Interest rate decision (FOMC statements) and QE announcements	Usually on Tuesday**	45 days**	13:15**	15:15 or 16:15**	US Federal Reserve (FED)	22***
	Price	Consumer price (CPI)	Wednesday or Friday	Monthly|	08:30	10:30 or 11:30*	Bureau of Labor Statistics	25
	Real Economy	Non-farm Payroll (PR)	Friday	Monthly|	08:30	10:30 or 11:30*	Bureau of Labor Statistics	19

Note: FOMC and COPOM are the central bank committees responsible for the decision on the short-term interest rates.
IPCA and PIM are the initials for the consumer price index and monthly industrial production in Brazil.
QE: Quantitative Easing
* The difference is due to differences in saving lights times.
** The periodicity and time information refer only to interest rate decisions by FOMC.
*** Includes four QE announcements.

At times, the blind analysis of an indicator is a noisy picture of the real state of the economy. If an apparently positive indicator, for instance, is contaminated by a one-time event, the surprise component should reflect this. That is why it is not unusual to see that good indicators drive down the market and the reverse is also true. Our indicators' measures are not free from such concern. Although we recognize this potential problem, markets take time to absorb and do not correct instantaneously in these cases. In addition, we do not know the exact time of the reversal effect, if any. Consequently, as we focus on the immediate market reaction, the raw indicator is the most adequate.

As far as expectations are concerned, Rigobon & Sack (2008) pointed out that they are noisy and hard to measure. As much as possible, it is important to capture expectations directly from market prices[7]. Otherwise, one should analyze carefully the survey's historical results; for instance, it is not a good signal if they always fail in one direction. In Brazil, the Central Bank releases a weekly survey (FOCUS Survey) that, besides showing the average perception of financial agents about some indicators, it also informs the average of the Top 5 agents, i.e., those who had the best recent forecasts. Hence, we will address this concern by using this specific indicator as we believe they provide better expectations measures.

Real economy and inflation surprise components will be calculated following Balduzzi, Elton & Green (2001), where the discrepancy between unit measures justifies the normalization procedure, also allowing a relative comparison between results.

$$S_{kt} = \frac{A_{kt} - E_{kt}}{\sigma_k} \qquad (1.3.2.1)$$

Where A_{kt} is the released value for announcement k, E_{kt} denotes its expectation and σ_k is each announcement standard deviation´s surprise. Time t is a discrete variable that indexes each announcement date.

Monetary surprise deserves a special attention as our database starts at the onset of the financial crisis of 2008. Since September 2007, Federal Reserve (FED) started to lower short term interest rates in response to a deteriorating state of the economy. At this point, however, interest rates were already close to zero, reaching the zero-bound at the December 2008 meeting and remaining there until the end of the database period. Following Lehmann Brothers' bankruptcy, FED not only continued its monetary easing but also set up a policy known as Quantitative Easing (QE) in order to respond to the crisis' collateral effects. This unconventional type of monetary policy involved the expansion of central banks' balance sheets aimed at influencing long-term interest rates directly. In 25th November 2008[8], FED announced the first QE, or QE1, where it would purchase treasury bonds and mortgage-backed securities (MBS) providing not only liquidity to a dry market but also affecting the term structure of interest rates. Shortly after the first announcement, in 1st December 2008[9], FED's release provided additional details concerning the purchase operations. Then, QE1 information is spread in time and in different releases from FED. Gagnon et al (2011) and Krishnamurthy & Vissing (2011) identified eight relevant communications related to QE1 assuming that markets are efficient and what really matters are the communications not the purchase operations. Besides the two events mentioned above, the other six are FOMC statements released after interest rate decisions that reveal QE1 information on volume, securities involved and purchasing period. Our sample period also encompasses the second round of QE, or QE2. We will follow Krishnamurthy & Vissing (2011) and include two[10] dates concerning QE2: 21st September 2010[11] and 03rd November, 2010[12]. The second round of quantitative easing was distinct from the first in that the aim was to support economic activity by reinvesting principal payments from agency debt and agency mortgage-backed securities that it had acquired in QE1 in longer-term Treasury securities. Thus, despite keeping balance sheet reserves unaltered, it did not resort to purchases of different sort of asset like in QE1, whose aim was to provide credit easing through large scale asset purchases, including private ones.

Since there were no expectations of a reversion on monetary easing, (1.3.2.1) implies a monetary surprise very close to zero when the target rate is considered. Moreover, Treasury bills, the shortest-maturity debt obligations issued by the U.S. government, are historically lower than Fed funds rate and reached the zero-bound even before December 2008. But remember that we are interested in the announcement impact and, in fact, statements released by FOMC reveals more than just the target fund, giving insights of the state of the economic and also

[7] Domestic and external interest rates expectations were measured from market prices.
[8] At 01:15 PM (GMT) or 11:15 AM(Local Time).
[9] At 06:45 PM (GMT) or 04:45 PM (Local Time).
[10] Krishnamurthy & Vissing (2011) suggested three dates, but 10th October 2010 is a missing data in our sample.
[11] At 03:15 PM (GMT) or 06:15 PM (Local Time).
[12] At 04:15 PM (GMT) or 06:15 PM (Local Time).

suggesting the future path of the target rate. In the meeting of January 28, 2009[13], for instance, Federal Reserve suggested that it would keep the target rate at the zero lower bound for a prolonged time, producing a widespread impact on the financial market. In this respect, Swanson & Williams (2013) investigated the effect of the zero lower bound on the term structure of interest rates and its responsiveness to macroeconomic announcements. The authors concluded that, between 2008 and 2010, monetary policy has been as effective as usual. Using study event methods with daily and intraday data, Neely (2010) also found that QE announcements substantially reduced long-term U.S. and foreign bond yields as well as the foreign exchange value of the dollar. In fact, FOMC meetings sustained its ability to impact long term maturity yields, producing daily variations in five and ten-year bonds compatible with sizeable "normal time" surprise changes in the federal funds rate, as calculated by Gürkaynak et al. (2005) and Glick & Leduc (2013).

Accordingly, shorter-term maturity bonds do not seem adequate to capture the monetary surprise component of a FOMC meeting, at least for the unconventional sample period under study. Moreover, QE announcements aimed at influencing long-term rates directly. In Wright (2012), monetary shock has been computed based on the first principal component of a set of bond futures traded at the Chicago Mercantile Exchange (CME), ranging from two to thirty years to maturity. We opted for a more traditional strategy, based on robustness checks. In our reference scenario, we have chosen a long-term maturity, the constant maturity ten-year Treasury bill, to measure the impact of a FOMC meeting release. As a robustness check, we will provide the results for the one-year and two-year contracts, all of them provided by FED. As we have only daily data on US bonds, the surprise component will be calculated as the difference between the closing rate on the FOMC/QE day and the day before, resting on the assumption that it is the main factor driving interest rates and that the risk premia is constant in between. We analyzed the economic calendar from 2008 to 2011 and could not identify any concurrent macroeconomic announcements released on a regular basis. Although we cannot rule out the effect of non-regular events, we will refer to Faust et al (2003) to assume that the correlation between the surprise taken from daily and intraday futures data nearby FOMC meetings is very close to one.

Since the zero-bound constrain do not apply to domestic monetary surprises, it will be calculated taking the 30-day interest rate swap contract. In the same line of reasoning, we will check the results with a one-year to maturity contract to account for a broader[14] impact of a COPOM meeting. In Table 4, we show the most relevant information on each indicator´s expectation.

[13] The FOMC stated: "The Federal Open Market Committee decided today to keep its target range for the federal funds rate at 0 to 1/4 percent. The Committee continues to anticipate that economic conditions are likely to warrant exceptionally low levels of the federal funds rate for some time."

[14] In Brazil, interest rate term structure is severely limited by a shorter investment horizon. In this sense, a year-contract can act as a medium to long term yield.

Table 4: List of expectation by indicator

Indicator	Description	Standard deviation	Source
COPOM	Closing rate of the short term interest rate swap contract (30 days to maturity) in the last day before announcement.	0,11	BM&F Bovespa
IPCA	Most recent survey	0,07	Central Bank of Brazil (FOCUS Survey)
PIM	Most recent survey	0,73	Central Bank of Brazil (FOCUS Survey)
FOMC	Closing rate of a long term Treasury bond (10-years to maturity) in the last day before announcement.	0,15	FED
CPI	Most recent survey	0,13	Bloomberg
PR	Most recent survey	94438	Bloomberg

The FOCUS survey provides market expectations on a daily basis about the Brazilian main economic indicators, including inflation rate and industrial production. In terms of forecasting performance, Lima & Alves (2011) found no significant evidence of the superior ability of FOCUS survey when compared with univariate autoregressive models. We must bear in mind, though, that it exerts a prominent role in the conduction of monetary policy in Brazil. Besides, it provides a standard deviation comparable to the one based on Bloomberg forecasts[15].

Graph 1 presents the evolution of the normalized surprises for all the six announcements. In Brazil, the Central Bank did not cut interest rates immediately after the Lehmann Brothers' event and the coordinated interest rate cuts held by central banks worldwide, in the last quarter of 2008. Only in the beginning of 2009, it started to cut interest rates aggressively even when inflationary pressures indicated otherwise. Hence, domestic monetary surprises were mostly negative up to the meeting of March 2010, when COPOM started a contractionary monetary cycle that lasted until the middle of 2011. The abrupt shifts in the conduction of monetary policy in such a short period of time explain the erratic behavior of COPOM surprises and reveal a disagreement between market and Central Bank expectations over the duration and intensity of each monetary cycle. Moreover, the fact that surprises are mainly negative shows that the market expected a more hawkish monetary policy than the one actually employed.

Prior to the financial crisis, Brazilian economy experienced high growth rates led mostly by consumer expenditures. With the decline in commodity prices and in consumer credit availability, there was a consensus that the external scenario would imply a deflationary price pressure. On the other hand, federal governments and central banks worldwide, including the Brazilian one, responded to the crisis with aggressive expansion of fiscal and monetary balances. Thus, there were two opposing driving forces at work with an unpredictable combined outcome. In fact, until mid-2009, the fact that IPCA and PIM[16] surprises were high shows that inflation and real economy indicators were harder to predict immediately after the crisis. We can also conclude that surprises' signal are rather persistent, revealing that market forecasts fail to predict and recognize persistent shifts in the level of those economic indicators.

Until mid-2009, QE and FOMC statements promoted a reduction in long-term bonds and, by assumption, its surprise component. Note also that the highest negative surprises refer to QE-related announcements. In 25th November, for instance, QE1 was launched by FED. In 18th

[15] Most high frequency studies take announcements' expectations from Money Market Services (MMS) forecasts, which we do not possess. Publicly available Bloomberg data present market consensus for CPI only in the first decimal place, what partially explains its relative high standard deviation figure.

[16] Remember that PIM announcement are lagged by two months. So, for instance, a January 2009 release refers to what happened in November 2008.

March 2009, FED's announcement that it would inject US$ 1 trillion to aid economy by buying treasury bonds and mortgage securities, generating a high negative surprise associated with a significant reduction in long term bonds. In the same period, CPI and PR surprises were mostly negative reflecting the uncertainties over the state of the economy and the difficulties surrounding the conduction of monetary policy.

Since the second semester of 2009, as the economy started to present signs of recovery of the economy, all external announcements exhibited a well-behaved pattern, characterized by fewer outliers and constant shifts between positive and negative ones, displaying minor error persistence.

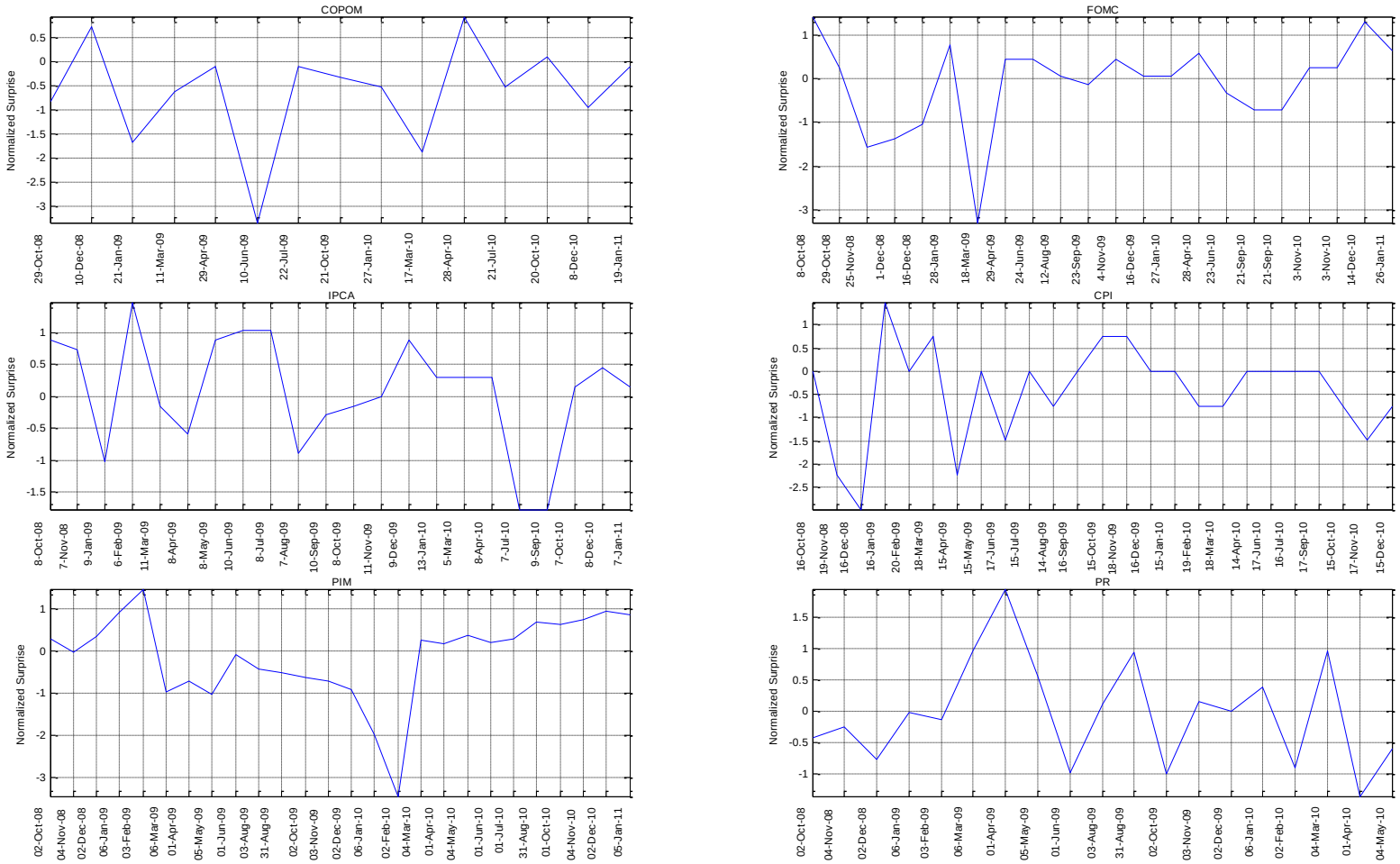
1.4.The model

The original database has information on returns, trading volumes and bid-ask spreads of the entire sample period, totaling 55,404 observations (513 days x 108 5-min intervals per day). In the spirit of the event study literature, we must be able to identify time periods around announcements so as to avoid concurrent effects on returns. More precisely, we must define an estimation window that must be wide enough to capture announcement effects but not so wide to allow returns to be affected through other channels.

Accordingly, we collected twenty 5-min returns around each announcement, two of them before and eighteen after it. The small interval before announcements is needed to identify, if any, the relative impact on returns. When announcements are released after the market is closed[17], we opted to consider the last two 5-min interval of the current day as the pre-announcement period and the eighteen first ones of the subsequent day as the post-announcement period. In this case, markets absorb the news during the night and there is no way to avoid a quicker adjustment in the morning. The same logic was applied to the cases when announcement is made at the first interval[18] of the day. With the selection procedure proposed above (see Figure 1 in Annex A for its graphical representation), the final database ended up with 2504 observations.

[17] COPOM announcements, for instance.
[18] IPCA and PIM are released at 09:00 AM, when markets are opening

Graph 1: Evolution of announcements' surprises



Let S_t^k be the surprise component of each announcement, our variable of interest. Following Andersen et al (2003, 2007), we propose a linear model in order to measure the short-term dynamics of the selected variables after macroeconomic announcements. We run different regressions, one for each market and independent variable, as follows:

$$R_t^h = \beta_0^h + \beta_1^1 . R_{t-1}^1 + \beta_1^2 . R_{t-1}^2 + \beta_1^3 . R_{t-1}^3 + \sum_{k=1}^{6} \sum_{j=0}^{3} \chi_{kj}^h . S_{t-j}^k + \varepsilon_t^h \qquad (1.4.1)$$

Where t refers to each 5-min interval, h refers to each market (IR=1, FX=2, Ibovespa=3) and k identify the six announcements described in Section 1.3.2. R_j^h are the returns of each market h. S_t^k takes the computed value at the first 5-min interval after the announcements and zero afterwards.

Andersen & Bollerslev (1998) already documented the existence of volatility spikes around macroeconomic announcements lasting approximately twenty minutes what validates the four-lag structure of the surprise variableS_{t-j}^k . This assumption is probably broken by QE announcements in that, according to Gagnon et al (2011), short estimation intervals are not able to capture the whole effect due the unconventional nature of this policy and its late assimilation from the market. To account for this, besides incorporating it in the intraday analysis (1.4.1), we will analyze QE effect in Section 1.5.1 using daily data. In model (1.4.1), we assume that surprise variables are exogenous. According to Christiano et al. (1998), monetary policy decisions can be viewed as the systematic response of policy makers to the state of the economy and the shock, its unaccounted or surprise component. Therefore, the exogeneity assumption also implies that both FOMC and COPOM meetings do not reveal any private information of the monetary authority. Note also that ARCH effects and cross market linkages[19] as long as we include lagged returns for all markets.

Since events are spaced in time, it is worth analyzing if the day breaks that arise from the selection procedure can cause any bias in the coefficient estimates. This would be true if we expected that observations outside the sample would bring information on the surprise variables. But remember that we assumed that the impact on the returns is short-lived. In other words, unless one thinks that our estimation window is not adequate, there is no reason to believe that there will be any bias in the regression estimates.

Due to the time-varying nature of the innovations ε_t^h, the Ordinary Least Square (OLS) estimation of model (1.4.1) would produce consistent, but inefficient coefficient estimates. We again follow Andersen et al (2007) and apply a two-step correction procedure for heteroskedasticity based on Weighted Least Squares (WLS). In the first step, we perform an OLS regression of (1.4.1), whose absolute residuals are used to estimate (1.4.2) as shown below. Finally, equation (1.4.1) is recalculated through WLS using (1.4.2) as the volatility weighting.

$$\left|\widehat{\varepsilon_t^h}\right| = \sum_{i=1}^{9} \beta_i^h \left|\widehat{\varepsilon_{t-i}^h}\right| + \sum_{j=1}^{9} \lambda_j D_t^j + \sum_{k=1}^{6} \sum_{j=0}^{3} \chi_{kj}^h D_{t-j}^k + \mu_t^h \qquad (1.4.2)$$

[19] Andersen et al (2007) also calculated contemporaneous spillover over effects applying heteroskedasticity identifying restrictions.

Where $\widehat{\varepsilon_t^h}$ is the first-step residual for each market h, D_t^j is the dummy that identifies each observation's hour and D_{t-j}^k is the announcement dummy that sets to one when observations are related to macroeconomic announcement k.

The first term of (1.4.2) accounts for serial correlation or ARCH effects and the second one, for the intraday volatility. Note that, contrary to Andersen et al (2007), we opted to control for the hourly volatility (nine trading hours per days) instead of using each 5-min intervals to avoid overparametrization. The last term controls for announcement-specific volatility patterns.

When we substitute the dependent variable in (1.4.1) by each market´s trading volume and spread, it is important to highlight that economic surprises are replaced by their dummy counterparts, a key modification to the original model[20]. Consider a public authority planning a neutral market intervention, i.e., one that is aimed only at restore supply and demand equilibrium. Suppose it wants to avoid periods in which there is a drop in liquidity, when it could induce noise and excess volatility. In contrast to high frequency traders seeking return premiums, the most relevant decision criteria for this kind of agent is the average effect of each announcement, as they will not plan an intervention based on information that they do not possess ex-ante, i.e., the direction of the surprise. The parameters of equations (1.4.3) and (1.4.4) will be also estimated by WLS.

$$X_t^h = \beta_0^h + \beta_1^1 . X_{t-1}^1 + \beta_1^2 . X_{t-1}^2 + \beta_1^3 . X_{t-1}^3 + \sum_{k=1}^{2} \sum_{j=0}^{3} \chi_{kj}^h . D_{t-j}^k + \varepsilon_t^h \quad (1.4.3)$$

$$\left|\widehat{\varepsilon_t^h}\right| = \sum_{i=1}^{9} \beta_i^h \left|\widehat{\varepsilon_{t-\iota}^h}\right| + \sum_{j=1}^{9} \lambda_j D_t^j + \sum_{k=1}^{2} \sum_{j=1}^{3} \chi_{kj}^h D_{t-j}^k + \mu_t^h \quad (1.4.4)$$

Where X can either refer to the bid-ask spread or to trading volume.

Spreads are derived following the same procedure as described in Section 1.3 and 1.4 for the returns, i.e., refers the last available value for each 5-min interval. They are computed as the relative difference between bid and ask values and measured in percentage points (p.p.). Trading volume refers to the sum of the number of traded contracts in each 5-min interval, respectively.

However, as Table 12 in Annex A shows, these variables present a pronounced seasonal pattern. Spreads reaches its peak inT the first two hours of the trading section and are relative stable afterwards. With respect to volume, we can define three different volume regimes. In the beginning of the trading session, we identify a high trading regime, followed by low volume in lunchtime and a new period of higher volume afterwards. Hence, we need to modify each 5-min variable in order to avoid bias in the results and we opt to compute spreads and volumes as a ratio relative to its correspondent hourly mean figures. According to this new definition, the

[20] Replicating model (1.4.1) to trading volumes and bid-ask spreads, with announcements' surprise as the independent variables instead of dummies, impact estimates were mainly insignificant. Given the persistent and widespread reactions observed in the latter case, we speculate that, although trading volume and bid-ask spread fluctuations are related to announcements, reactions are not correlated to the surprise components.

coefficients must be interpreted correctly as the relative announcement impact to the hourly mean on spreads and volume.[21]

1.5.Results

According to equations (1.4.1) and (1.4.3), the effect of macroeconomic announcements in the futures market is measured within a twenty-minute post-release window, split in four 5-min intervals. We will derive our measures of interest based on the aggregate effect by summing up coefficient estimates in a progressive aggregation up to twenty minutes. In formal terms, as follows:

$$Five - minute\ aggregation: H0:\ \chi_{k0}^{h} = 0$$

$$Ten - minute\ aggregation: H0:\ \chi_{k0}^{h} + \chi_{k1}^{h} = 0$$

$$Fifteen - minute\ aggregation: H0: \chi_{k0}^{h} + \chi_{k1}^{h} + \chi_{k2}^{h} = 0$$

$$Twenty - minute\ aggregation: H0: \chi_{k0}^{h} + \chi_{k1}^{h} + \chi_{k2}^{h} + \chi_{k3}^{h} = 0 \qquad (1.5.1)$$

Where h refer to each market and k for the announcements. The indexes (0,1,2,3) refer to the five, ten, fifteen and twenty minute surprise coefficient estimates calculated as (1.4.1) and (1.4.3). The p-values will be computed by means of a Wald Test on each aggregate effect.

First of all, we want a measure of speed or <u>how fast</u> each market reacts to each announcement. The surprise component of an announcement is equivalent to the release of a new public information. According to the semi-strong form of efficient market hypothesis, it should be instantaneously reflected in asset prices. We will derive this information by identifying the first joint coefficient that is significant at some pre-specified level of significance. Another important aspect to be assessed is the persistence effect, or <u>how long</u>[22] will the announcement be an explanatory factor. An overreacting market could respond instantaneously to a surprise and, in the next interval, adjust to the previous price level. More efficient markets are expected exhibit a more persistent pattern, i.e., once reacting to a surprise it will sustain its price levels until the 20-min aggregation. So, the last significant joint coefficient will be used to analyze this effect. Finally, the value of the last significant joint coefficient is a direct measure of intensity, or <u>how much</u> does the surprise affect each market.

The direction of the return changes deserve a particular attention in order to compare with what one could expect by applying basic economic thinking. For the sake of simplicity, it is important to highlight that we will take into account what we consider to be the dominant factors surrounding price determination in each market to derive the most likely impact of the announcement surprises.

Since 1999, Brazilian monetary authority runs an inflation targeting approach for the conduction of monetary policy. Consider a general interest rule function:

$$i_t = \gamma_\pi E_t(\pi_{t+\tau}) + \gamma_y E_t(y_{t+\tau}^{*}) \qquad (1.5.2)$$

[21] We also modeled the intraday behavior of trading volume and bid-ask spreads using cubic splines with hourly knots. Under this alternative model, impact estimates were mainly insignificant. We attribute the contrasting results to the fact that splines potentially add noise to the high frequency observations, contrary to our proposed specification, that preserves the proportionality between sequential observations.

[22] Persistency is frequently measured in the literature with the half-life criterion. Our first-order serial correlation, however, is not high enough to allow its application in the present study.

Where γ_π and γ_y are positive weights on inflation and output gap expectations, respectively, and τ is the monetary policy horizon.

According to our definition, a positive monetary surprise is meant by a higher target rate than the one implied by (1.5.2). To derive the expected effect of a monetary surprise on futures interest rates, we must first understand its association with the yield curve. According to Litterman & Scheinkman (1991), there are three common sources driving the term structure of interest rates: level, steepness, and curvature. Since most part of the variation (89.5%) can be attributed to the level factor, an unexpected rise in the short run interest rate should, everything else constant, raise interest rates for all expiration dates. However, the authors showed examples where ignoring the other two factors' impact can lead to severe loss in hedged portfolios. Assuming that risk premium is not altered in our short interval window, the expectations theory of the term structure of interest rates states that the yields on financial assets of different maturities are related primarily by market expectations of future yields. A negative monetary surprise, for instance, can reveal that BCB is less concerned about inflation (equivalent to a reduction in γ_π in equation 1.5.2) what will make short term rates to fall and long term ones to rise at some point so as to reverse the current expansionary effect. Such shocks may have the power to change the slope of the yield curve, corresponding to the steepness factor described by Litterman & Scheinkman (1991) as the one that is an increasing function of time to maturity. The effect on medium-term interest rates, our object of interest, depends on the extent of which the market expects the monetary easing to last and, thus, we are not able to unambiguously determine the sign impact[23]. Instead, we will reverse the argument and infer the expectation of the market on the monetary cycle by the estimated impact in the IR market. Real economy surprises are expected to positively related to medium term interest rates since they can anticipate future reversals on the monetary cycle. In face of positive inflation surprises, we expect the level factor to be dominant and, hence, interest rates to rise. When we only consider the expansionary cycle, a positive monetary surprise can reveal a higher than expected weight on inflation[24] generating an asymmetric effect on interest rates but, once more, we also cannot determine ex-ante the inflexion point of the yield curve. On the other hand, positive real economy surprises raise interest rate as long as the decreasing output gap may potentially be converted into inflationary pressures.

It is true that, according to (1.5.2), external announcements should only affect the IR market as long as they produce changes in inflation or real economy expectations. But the instantaneous effect is better understood when one analyzes the effect of interest rate differentials on the demand for domestic bonds which we assume to be the main transmission channel in the short run. External investors have a large participation in the IR secondary and futures market in Brazil. A positive US monetary surprise, usually associated to a stronger than expected economy, trigger the reallocation of portfolio investments around the world to the US bonds. The drop in demand for domestic bonds reduces its prices and raise interest rates levels for all maturities with different intensities. The same impact is expected when inflation and output surprises are positive since they both raise the level of US interest rates.

In order to analyze the impact on the FX market, Engel & West (2006) and Engel (2013) provide a suitable framework. The authors set up a two-country specification where uncovered interest rate parity holds and both countries follow a general interest rule with an additional term to equation (1.5.2) that allows for interest rates to react to exchange rate misalignments. Within short time intervals, real exchange rates can be substituted by nominal ones, generating the following model:

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[23] Empirical studies on the Brazilian term structure showed conflicting results over the effect of steepness shocks. Luna (2006) showed that factor loadings, associated with medium-term contracts, were very close to zero. By contrast, Shousa (2008) and Bressan et al (2007) showed that factor loadings were already close to zero for short term contracts, with six months to maturity.

[24] We assume that no private information is revealed in COPOM meeting that could change market´s perception on inflation and output gap expectations.

$$s_{t+\Delta} - s_{t-\Delta} \approx -\sum_{j=0}^{\infty}\left(\frac{1}{1+\gamma_q}\right)^j (E_{t+\Delta} - E_{t-\Delta})\left\{\left(\frac{\gamma_\pi - 1}{1+\gamma_q}\right)(\pi_{d,t+j+1} - \pi_{e,t+j+1}) - \left(\frac{\gamma_y}{1+\gamma_q}\right)(y^*_{d,t+j} - y^*_{e,t+j})\right\}$$
(1.5.3)

Where the time period is one-month, Δ is our 5-min interval and $(y^*_{d,t+j}, y^*_{e,t+j})$ and $(\pi_{d,t+j+1}, \pi_{e,t+j+1})$ are the domestic and external output gaps and consumer inflation indexes, respectively. The factor γ_q is the additional term in the home interest rule related to exchange rate misalignment.

Assuming that the central bank follows a sufficiently stabilizing monetary policy $(\gamma_\pi > 1, \gamma_q, \gamma_y > 0)$, model (1.5.3) implies a positive correlation between expected inflation and output gap in the home country to domestic currency appreciation. Also, higher inflation and higher output gap in the foreign country leads to domestic currency depreciation. The effect of interest rate surprises is equivalent to inflation or output gap one in that they are positively linked through the Taylor rule. These predictions are consistent with the analysis of the short-term equilibrium between dollar supply and demand since positive prospects of the US economy that become evident from whatever the source (monetary, inflationary or from the real economy should lead to home currency depreciation as long as the dollar supply decreases. These theoretical considerations are validated by some empirical works on the high frequency impact of announcements. Clarida & Waldman (2008) found that the positive correlation between inflation expectations and exchange rates is stronger in countries that follow inflation targeting rules. Recent studies (Andersen et al (2007), Faust et al (2007)) related a stronger than expected economy with dollar appreciation, equivalent to home currency depreciation.

The relationship between economic news and stock prices are harder to predict. In the simple dividend model (1.5.4) where risk premium is assumed to be constant in short intervals, stock returns are a function of dividend flow and the cost of equity. Economic news can convey information on both factors and its relative importance can vary depending on the state of the economy. Accordingly, a rise in cost of equity originated by a monetary or inflation surprise should decrease the value of dividends and, everything else constant, reduce the amount invested in stocks to bonds. Positive real economy surprises increase future dividend returns, rising stock valuation and prices.

$$y = f(E_t\left(\sum_{j=1}^{\infty} d_{t+j}\right), i_t^e), \frac{\partial y}{\partial E_t\left(\sum_{j=1}^{\infty} d_{t+j}\right)} > 0 \; \frac{\partial y}{\partial i_t^e} < 0 \qquad (1.5.4)$$

Where $E_t(\sum_{j=1}^{\infty} d_{t+j})$ are the expected future dividends and i_t^e, the cost of equity.

Finally, the effect of external announcements on stock market has two opposing dimensions. On one hand, we have seen that a stronger than expected US economy raise both US and domestic interest rates drive investment flows to the central economy and reducing the present value of dividends. However, it has a positive effect on the dividend flow provided that a wealthier international economy is a positive factor for domestic companies. Thus, the sign impact shall depend on the relative intensity of such dimensions. In Table 5 below, we summarize the theoretical predictions discussed above.

Table 5: Theoretical sign of impact per announcement on IR, FX and Ibovespa futures returns

	IR	FX	Ibovespa
COPOM	NA	-	-
IPCA	+	-	-
PIM	+	-	+
FOMC	+	+	NA
CPI	+	+	NA
PR	+	+	NA

Note: NA: Not assigned.

Although common sense points to a positive relationship between price and volume reactions, Bamber and Cheon (1995) find evidence of public announcement with small price changes and high trading volume. Actually, nearly a quarter of firm-specific earnings announcements generate divergent reactions in terms of magnitude. Accordingly, there is a literature aimed at providing answers of what can be inferred from public announcements by its trading volume.

Empirical studies already documented that announcements increase trading volume in different markets. Balduzzi, Elton & Green (2001), for instance, documented significant and persistent post-announcements increases in trading volume in the interdealer broker market for US bonds. Concerning the FX market, Chaboud et al (2004) also reported a sharp increase in trading volume after US announcements in the Global interdealer spot market. Basically, two factors were identified as important drivers to trading volume. The first one is that public announcement provides the grounds to uncertainty resolution implying that trading volume prompted by a public announcement is positively related to the announcement's precision. In some theoretical models of trade, such as Blume et al (1994), information quality is deduced from volume and considered an informational advantage in investment strategies such as technical analysis. Barron & Karpoff (2004) note, however, that this interpretation does not always holds as transaction costs can interfere in this positive association. A more recent strand of the literature focus on the fact that markets are composed of heterogeneous agents with differential public announcements' interpretations. This divergence not only stimulates speculative trading but also gives rise to the “no price, high volume reaction” described in the literature. With that in mind, our main task will be to infer the microstructure of each market based on the regression results. Besides, the relative magnitudes can be used to determine the relative information content of each announcement.

As liquidity can be related to information asymmetry, the effect on spreads will be confronted to trading volume in order to assess this relationship. Kyle (1985) has shown that asymmetric information is positively related to illiquidity. Considering that spreads are a market maker´s protection from informed trading, informed traders lose the camouflage from noisy trading in low liquid markets. All else equal, though, profits based on inside information trading can be maximized in a frequently traded asset. So, according to Kyle´s model, market makers increases ask prices to protect from huge order flows from informed traders. BVMF order-to-order trading system, however, does not include market makers and the protection against the action of informed traders is possible through limit orders. In view of this framework, trading volume and spreads should present a negative association.

We additionally want to check for business cycle singularities. In the first months that followed the peak of the financial crisis, Brazil suffered a dramatic turnaround in its economic prospects. The first sign of recovery did not appear until the second quarter of 2009 with the release of a positive quarterly GDP after two consecutive positive industrial production indicators. The contraction period, thus, should comprise observations from October 2008 to

March 2009, while the expansion one from April 2009 to January 2011. Note, however, that such definition would yield a very short contraction sub-sample, with few observations. We will partially circumvent this problem by running two regression sets, one for the full sample and another for the expansion period. Differences in the results will then be associated with state dependency.

1.5.1.The impact of macroeconomic announcements on returns

Rather than commenting on the regressions individually (see Table 13 in Annex A), I organize the most interesting aspects of the empirical results in terms of the three indicators mentioned in the beginning of Section 1.5: how fast (efficiency), how long (persistence) and how much (intensity). With that in mind, Table 6 displays the response of each market to the surprise component of the selected macroeconomic announcements. In general, when a significant impact is verified, markets react quickly at the first 5-min interval. In most cases, however, we observe price reversions given that only few announcements show persistent effects up to the twenty-minute estimation window.

At the IR market, in particular, responses are not only fast but short-lived as well. Reactions to FOMC and PR surprise components, for instance, vanish after five minutes. Even COPOM and IPCA, the most important domestic news related to monetary decisions, keep its influence only up to ten minutes time. At this point, it should be noted that COPOM´s releases happen when markets are closed what surely alter the dynamics of information absorption relative to other announcements. In principle, it should increase the immediate impact and obscure potential changes in level attributed to COPOM, justifying the low persistence observed in the results. IPCA releases, which anchor COPOM decisions, mattered only in the expansion period, suggesting that the economic interpretation of macroeconomic news is ambiguous and depends on the cyclical position of the economy. The fact that expansion´s period R^2 is superior to full sample ones (see Table 13 in Annex A) for all market provides additional support to the procedure that splits sample according to the business cycle. Remember that our sample starts at the beginning of 2008's financial crisis. As such, expectation over the state of the US economy determined the evolution of long term interest rates. Moreover, policy makers expected a future deceleration of inflation indexes due to the colder economy and lower commodity prices. In the expansion period, however, domestic announcements were back to stage, since monetary authority decisions were not bounded by the external scenario.

FX and Ibovespa markets, in turn, react mostly to external indicators. The FX market display immediate reactions to the surprise components of COPOM, PR and FOMC, but only the latter is persistent up to twenty minutes. The results for Ibovespa reveal that it is the futures market that exhibits the most widespread reaction to announcements in terms of persistence as long as the impact of COPOM, FOMC and PR are significant at the 5% level up to twenty minutes.

By contrast, PIM and CPI have negligible impact on the futures markets for all announcements and at all perspectives. Take the example of PIM, which is a one-month lagged industrial production announcement and we assumed that its surprises could induce changes in market´s expectations over the output gap and real economy prospects. The "no impact" of PIM, thus, can be attributed to a fail in this assumption. CPI's lack of impact has another interpretation and rests on the fact our sample period covered a period in which US policy makers assigned a relative low importance to inflation due to the financial crisis.

Table 6: Impact of macroeconomic announcements on each futures market on returns

How fast

	IR		FX		Ibovespa	
	Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
COPOM	5 min	5 min	5 min	5 min	5 min	5 min
IPCA	No impact	5 min	5 min	No impact	No impact	No impact
PIM	No impact	No impact	No impact	No impact	5 min	5 min
FOMC	5 min	5 min	5 min	5 min	5 min	5 min
CPI	No impact	No impact	No impact	No impact	No impact	No impact
PR	5 min	5 min	5 min	5 min	5 min	5 min

How long

	IR		FX		Ibovespa	
	Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
COPOM	10 min	10 min	5 min	5 min	20 min	20 min
IPCA	No impact	10 min	5 min	No impact	No impact	No impact
PIM	No impact	No impact	No impact	No impact	5 min	5 min
FOMC	5 min	5 min	20 min	20 min	20 min	20 min
CPI	No impact	No impact	No impact	No impact	No impact	No impact
PR	5 min	5 min	5 min	5 min	20 min	20 min

How much

(Reported coefficients are expressed in percentage points for a unit shock. A unit shock from COPOM and FOMC is equal to 25 basis points; IPCA and CPI: 0.10 p.p.; PIM: 1.0 p.p.; PR: 100,000 jobs.)

	IR		FX		Ibovespa	
	Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
COPOM	-0.128	-0.107	-0.055	-0.071	0.173	0.094
IPCA	No impact	0.041	0.047	No impact	No impact	No impact
PIM	No impact	No impact	No impact	No impact	0.023	0.046
FOMC	0.029	0.029	0.191	0.089	-0.329	-0.313
CPI	No impact	No impact	No impact	No impact	No impact	No impact
PR	0.032	0.028	-0.045	-0.051	0.151	0.182

Note: All the estimates consider a 5% level of significance.
Coefficients were normalized to facilitate interpretation.

In addition to identifying the existence of a measurable announcement effect, it is important to clarify the direction of such effects and compare it with the theoretical expected signs of Table 5. In the IR market, we find an excess return of -0.107 p.p. in response to a 25 basis points' COPOM surprise and 0.041 p.p. in response to a 0.10 p.p. IPCA surprise. Both impacts are persistent up to ten minutes in the expansion period. Suppose Central Bank underreacts to inflation expectations, medium-term interest rates are expected to rise because the financial market expects inflation figures to rise accordingly imposing a new monetary

contraction cycle to start earlier than previously expected. Until mid-2010, domestic monetary policy experienced a shift in the reaction function while Central Bank implemented a progressive decline in the prime interest rate, Selic. At this period, it was less reactive to current inflation pressures and confident that a deflationary external scenario would bring inflation expectations down, as extensively documented by COPOM minutes and quarterly inflation reports.

There are several ways that underreacting to inflation expectations could negatively affect medium-term yields, as implied by our results. Investors possess long-term bonds and, according to its portfolio composition, are subjected to various degrees of duration risk. Duration generally refers to the approximate percentage change in a security's price that will result from a change in its yield. Since futures interest rates directly affect bond yields, the longer a bond's duration, the more sensitive its price is to changes in the IR futures market. In such a case that the IR market does not totally agree with the scenario proposed by monetary authorities, rising inflation expectations deteriorates medium and long term bond prices, while the opposite happens in terms of yields. Liquidity is another transmission channel that may offer a suitable explanation. In periods characterized by high uncertainty levels, investors usually shift portfolio composition towards short-term bonds. The resulting lower demand for longer term bonds produces higher interest rates. Also, another potential driving factor is Brazilian financial market´s perception that the worldwide commitment to keep interest rates low prevailing at the sample period could induce a low interest rate regime in Brazil, for more time than would be recommended in view of the domestic inflation figures and expectations.

The same rationality applies to a higher than expected IPCA when IR futures rates rise anticipating a tighter stance of monetary policy by COPOM. Both FOMC and PR surprise component estimates reveal an increase in futures interest rates when subjected to a positive shock, suggesting that a better than expected US economy drive interest rates up. But both impacts are short-lived reinforcing the dominance of domestic factors in the IR market.

Taking into account previous studies (Kolscheen (2011, 2012)[25]), it is not surprising to find that the FX market is sensitive only to FOMC announcements while the domestic ones showed only transitory or non-existent impacts probably due to the important role of external investors[26]. In effect, Fratzscher (2011) finds that domestic interest rate changes have no significant effect for explaining capital flow to Latin America both during the crisis period or afterwards. In both samples, FOMC is the main factor driving returns when a 25 basis points' surprise raises FX returns in 0.191 p.p. and 0.089 p.p. in the full sample and expansion period, respectively. So, an unexpected increase in US long-term interest rates appreciates the dollar relative to the domestic currency (BRL). External announcements are primarily responsible for changing the volume and direction of investment flow to the domestic economy. In this sense, higher interest rates or a better state of the economy takes liquidity away from emerging countries and leads to dollar appreciation, agreeing with Andersen et al (2007) and Faust et al (2007) findings. If we extrapolate this conclusion to the most recent monetary events, our results show that news related to the tapering of the stimulative quantitative easing policy by Federal Reserve shall appreciate dollar. That is exactly what Aizenman et al (2014) found, applying a panel framework using daily data between November 2012 and October 2013, for a group of 26 emerging countries.

In the same line of reasoning[27], Ibovespa futures are directly and persistently affected by two external announcements: FOMC and PR. A 25 basis points' FOMC surprise impacts stock futures returns by -0.329 p.p. and -0.313 p.p. in the full sample and expansion periods, respectively. Hence, a monetary policy easing is related to positive returns in Brazil, consistent with Aizenman et al (2014) which found that FOMC QE news were strongly associated with positive stock market returns in countries experiencing current account deficits, Brazil included.

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[25] Using event study based on daily data for Mexico, Brazil and Chile, Kolscheen (2011) also finds no significant relation between monetary surprises and exchange rates around monetary policy committee meetings. In a regression-based analysis, taking order flow and a set of economic variables as exogenous variables, Kolscheen (2012) have found no significant effect of interest rate differentials on exchange rate.

[26] In general, external investor account for approximately 15% of the FX traded futures contracts. However, their importance grows considerably when we net investors' position with the spot market.

[27] Approximately 50% of the Ibovespa futures contracts belong to external investors.

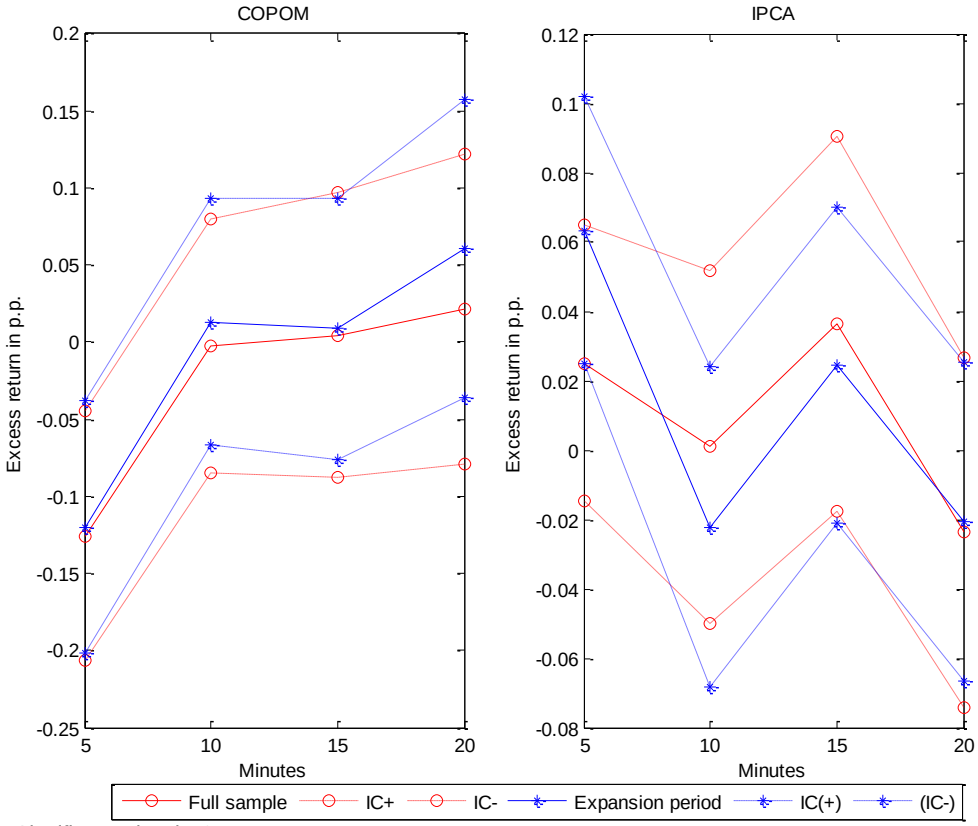
Non-farm payroll figures emerge as an important announcement and its surprise component is positively associated with domestic stock index returns. PR is persistent at both periods, when a 100,000 jobs' surprise increase returns in the stock market by 0.151 p.p. and 0.182 in the full sample and expansion period, respectively. It suggests not only that the dividend effect is higher than the cost of capital one but also that real economy shocks are correlated between Brazilian and US economies. This is in contrast with the results of Boyd, Hu & Jagannathan (2005) which found that unemployment rising is good news for the US stock market at the expansion period. We find support to our results when we take the study of Elder et al (2012), which find positive effects of an unexpected improvement of the US economy on copper prices using intraday data from 2002 to 2008, together with the high weight of commodity-related stocks in the composition of Ibovespa. Finally, a COPOM surprise amounting to 25 p.b. raise Ibovespa futures returns by 0.173 p.p. and 0.094 p.p. in the full sample and expansion period estimates, respectively. The positive correlation is at odds with the theoretical results in Table 5. Our interpretation is that the sensitivity of Ibovespa futures to a domestic monetary shock may owe to more than just the adjustment of the cost of capital: revision of expectations over central bank independency and commitment to policy rules may play an even more important role, assigning a greater impact of monetary decisions to the dividend effect of equation (1.5.4). More importantly, impact is found to be highly persistent up to twenty minutes after market opening. In view of to this prolonged effect if compared to the one observed in the IR market, we can conjecture that a COPOM shock primarily affects the IR Market and, after stabilizing it, it is then transmitted to Ibovespa futures contracts.

To sum up, focusing our attention to the most persistent announcements, we conclude that results match those predicted by theory and are robust to sample changes, as there are no sign reversals and minor differences in the intensity coefficients. Despite this general conclusion holds, state dependency can interfere in its relative magnitude and cancel out predicted impacts. The fact that IPCA estimates are conflicting over different samples is an indication of such effect, exactly as reported by Andersen et al (2007). By forming the full sample by adding observations from the contraction period to the expansion period, the coefficient that measures the impact of IPCA announcements is not significant at the 5% level. This is in contrast with the result obtained by restricting the sample to the expansion period, where the IPCA coefficient is positive and persistent up to ten minutes after the release. This result suggests that the contraction period, not included as a separate sub-sample only due to the small amount of observations, can generate sufficient noise so as to eliminate the significance of this coefficient. In fact, from October 2008 to March 2009, considering that worldwide financial systems experienced severe liquidity shocks, monetary authorities were less concerned about inflation and directed monetary policy instruments mainly towards preserving the functionality of the banking system.

In addition to the aggregate effect, it is worth analyzing the behavior of the 5-min coefficients in some selected situations. The general pattern is of an immediate conditional mean adjustment, characterized by a jump immediately following the announcement release, and no significant reaction thereafter. Aggregate effects, computed as the sum of the coefficient estimates, are persistent providing that quick reactions are not overturned in the remaining intervals. Graph 2 displays that COPOM surprises are significant only in the first 5-min interval for both sample estimates in the IR market. Adjustment to IPCA surprise, instead, occurs only in the expansion period, also limited to the first 5-min interval.

Graph 2: Estimated impact of Copom and IPCA on the IR futures market in each 5-min interval after announcement release per unit shock

(A unit shock from COPOM and FOMC is equal to 25 basis points; IPCA and CPI: 0.10 p.p.; PIM: 1.0 p.p.; PR: 100,000 jobs.)

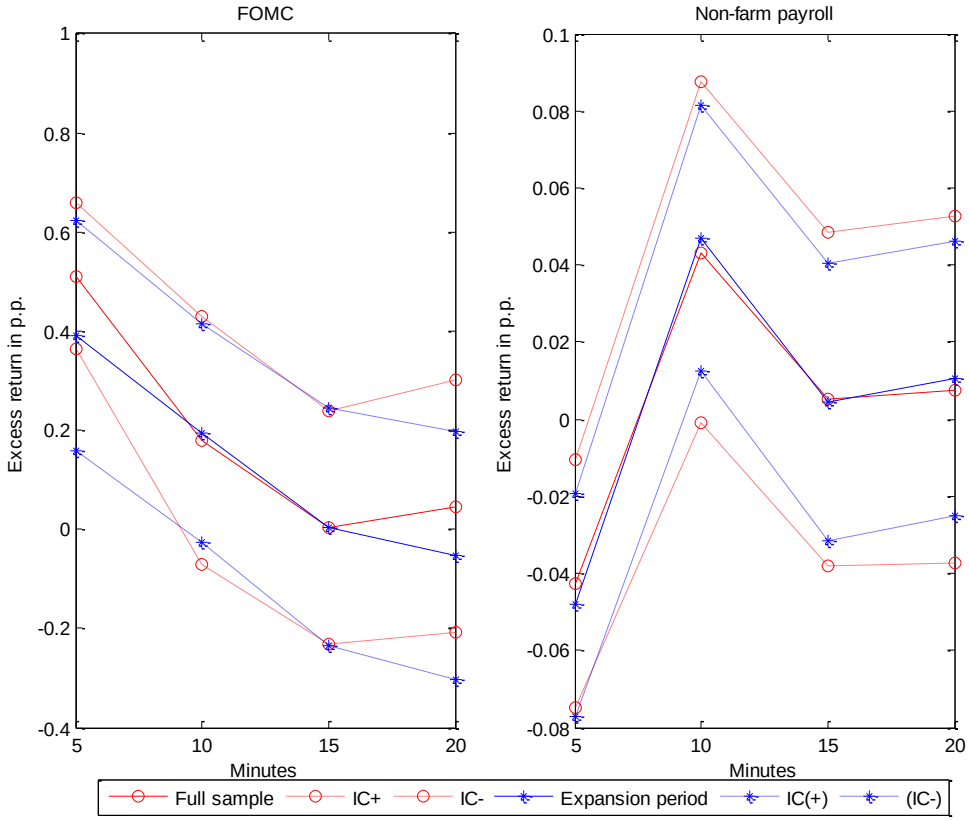


Note: Significance level: 5%

In the FX futures market, FOMC surprises are immediately incorporated into prices in both sample estimates, where the sign coefficient is meant by a positive correlation between 10-year US Treasury yields and USD appreciation (or BRL depreciation). As far as PR is concerned, we see that in both samples, the first reaction of the market is to appreciate dollar in response to a positive PR surprise, which means that a stronger economy with higher payroll figures appreciate dollar, exactly as implied by theory. But this effect is transitory as the FX market immediately reverse this trend it in the next interval.

Graph 3: Estimated Impact of FOMC and PR on the FX futures market in each 5-min interval after announcement release per unit shock

(A unit shock from COPOM and FOMC is equal to 25 basis points; IPCA and CPI: 0.10 p.p.; PIM: 1.0 p.p.; PR: 100,000 jobs.)

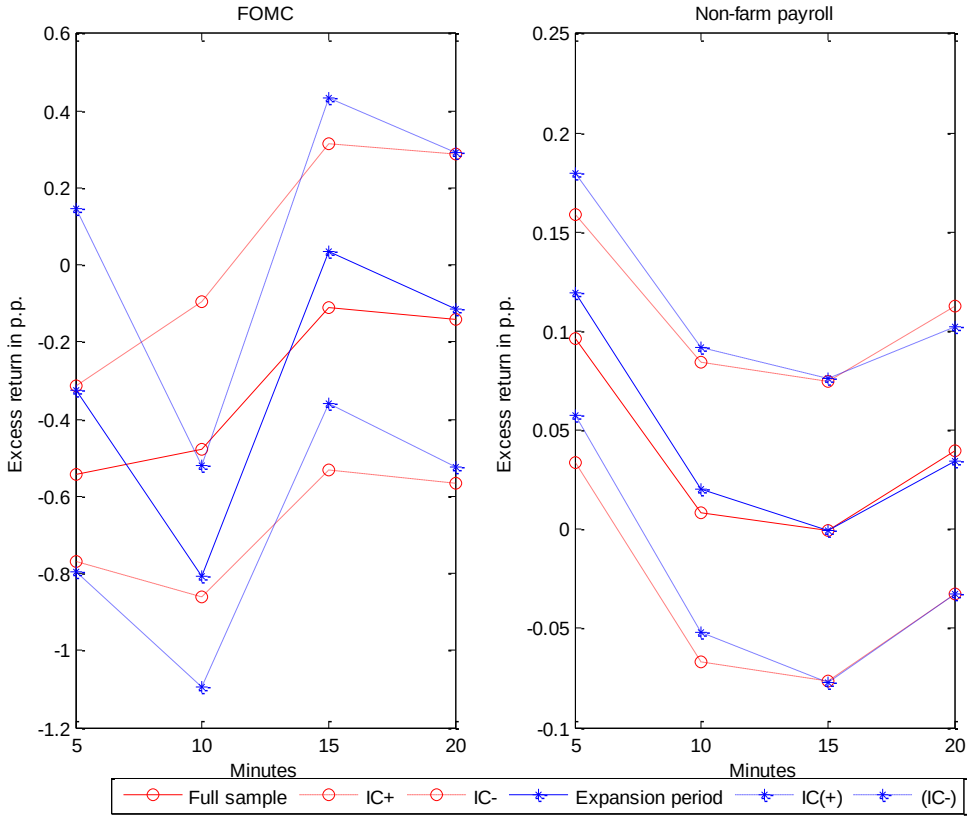


Note: Significance level: 5%

At Ibovespa market, a negative FOMC surprise, or conversely, financial market´s expectation that lower external interest rates will hold for a prolonged time is positive to domestic stock index returns. Its individual coefficient estimates are significant up to ten minutes after the announcement release, in contrast to the other markets. PR surprise affects the stock market in both samples with a similar pattern as the one observed in the previous examples, where adjustment occurs in the first 5-min interval.

Graph 4: Estimated impact of FOMC and PR on the Ibovespa futures market in each 5-min interval after announcement release per unit shock

(A unit shock from COPOM and FOMC is equal to 25 basis points; IPCA and CPI: 0.10 p.p.; PIM: 1.0 p.p.; PR: 100,000 jobs.)



Note: Significance level: 5%

1.5.2.Impact of macroeconomic announcements on trading volume and spreads

Consistent with previous results in the literature, there is no straightforward connection between trading volume and returns changes since there are announcements that do not impact returns at all but impact trading volume, and vice-versa. PIM and CPI, for instance, have an important overall effect on trading volume with no corresponding impact on returns. In the FX and Ibovespa markets, trading volume is affected by all external announcements in the first 5-min interval for both estimates. Impact on the IR trading volume, in turn, is dominated by domestic announcements although CPI and PR produce changes in terms of trading volume. Macroeconomic announcements are also economically important in explaining trading volume as we can infer by analyzing goodness of fit through its R^2 levels presented in Table 14 in Annex A.

From Table 7, it is also noteworthy to determine that impacts, when significant, are highly persistent up to twenty minutes after the release. Due to agent heterogeneity, liquidity trading shall occur in stages, with investors performing trades at different times leading to an impact on trading volume that is spread over the post-announcement window.

Table 7: Impact of macroeconomic announcements on each futures market on trading volume

	IR		FX		Ibovespa	
How fast						
	Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
COPOM	5 min	5 min	5 min	5 min	5 min	5 min
IPCA	5 min	5 min	No impact	No impact	5 min	5 min
PIM	5 min	5 min	5 min	5 min	No impact	No impact
FOMC	No impact	No impact	5 min	5 min	5 min	5 min
CPI	5 min	5 min	5 min	5 min	5 min	5 min
PR	5 min	5 min	5 min	5 min	5 min	5 min
How long						
	IR		FX		Ibovespa	
	Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
COPOM	20 min	20 min	20 min	20 min	5 min	5 min
IPCA	20 min	20 min	No impact	No impact	5 min	5 min
PIM	20 min	20 min	20 min	20 min	No impact	No impact
FOMC	No impact	No impact	20 min	20 min	20 min	20 min
CPI	20 min	20 min	15 min	20 min	5 min	5 min
PR	20 min	20 min	20 min	20 min	20 min	20 min
How much						
(Reported coefficients are expressed considering the seasonal adjustment proposed in Section 1.4. The coefficient unit, thus, is the hourly average trading volume prevailing at the time of the announcement release.)						
	IR		FX		Ibovespa	
	Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
COPOM	3.34	3.92	0.95	1.61	0.25	0.38
IPCA	2.05	1.64	No impact	No impact	-0.19	-0.23
PIM	0.99	1.11	1.05	1.39	No impact	No impact
FOMC	No impact	No impact	1.55	1.88	2.25	2.43
CPI	0.17	1.4	0.53	0.66	0.32	0.32
PR	1.27	3.13	2.04	2.13	1.56	1.79

Note: All the estimates consider a 5% level of significance.

Note that the surprise component of COPOM increases the number of traded contracts in the IR market by 3.34 and 3.92 relatively to the hourly average, respectively, in the full sample and expansion period estimates. If we deseasonalize the data, the increase in the number of traded contracts amounts to 4,880 and 5,730, respectively. If we refer back to theory, one can associate such remarkable result to COPOM's high information precision and its success in solving agents' uncertainty. One caveat, however, is that FOMC surprises are largely

insignificant during the observation period, a counterintuitive finding when confronted with the importance of FOMC-related news that deserves further investigation. As far as the FX and Ibovespa markets are concerned, the dominant role is performed by FOMC and PR surprises. In the expansion estimates, FOMC raises FX and Stock trading volumes by 1.88 and 2.43 times relatively to the hourly average, respectively, while PR impact is in the same order of magnitude. Besides market microstructure considerations, the superior informational quality of the dominant announcements can also stimulate trading.

From Table 8, we can see that spreads are affected mainly by domestic announcements where impact is immediate in the vast majority of situations. Taking trading volume as a proxy for liquidity, the association between liquidity and spreads is not confirmed as the increase in spreads is not accompanied by a reduction on trading volume.

Equally important is the fact that external announcements have little, if any, impact on spreads. We refer to Balduzzi, Elton & Green (2001) in order to provide an explanation for this finding. The quick reversion of bid-ask spreads, not captured by our 5-min data frequency, can be attributed to the dominance of informed trading in an initial trading phase. Such view can be reconciled with price impact figures (Graphs 3 and 4), where coefficients are only significant in the first interval. The persistence of trading volume beyond spreads' reversion is an evidence of a second trading phase where liquidity trading is prevailing, what supposedly occurs when markets face domestic announcements.

Assuming that spread increases are related to the presence of informed traders, why should this informational advantage be persistent for domestic announcements? It is realistic to infer that external announcements are more difficult to forecast and interpret by domestic traders, reducing the proportion of informed traders in relative terms. At the full sample, COPOM, IPCA and PIM raise IR market spreads by 0.61, 1.19 and 1.21 times[28]. In the FX and Ibovespa markets, estimates share the same signals and orders of magnitude. Individual regression results are shown in Table 15 in Annex A.

[28] Again, relative to the hourly average spread.

Table 8: Impact of macroeconomic announcements on each futures market on spread

	IR		FX		Ibovespa	
How fast						
	Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
COPOM	5 min	5 min	5 min	5 min	5 min	20 min
IPCA	5 min	5 min	5 min	5 min	5 min	5 min
PIM	5 min	5 min	5 min	5 min	5 min	5 min
FOMC	5 min	10 min	5 min	5 min	No impact	No impact
CPI	No impact	No impact	No impact	No impact	No impact	No impact
PR	5 min	5 min	5 min	5 min	5 min	No impact
How long						
	IR		FX		Ibovespa	
	Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
COPOM	20 min	No impact	20 min	20 min	20 min	20 min
IPCA	20 min	20 min	20 min	20 min	20 min	20 min
PIM	20 min	20 min	20 min	20 min	20 min	20 min
FOMC	20 min	10 min	20 min	20 min	No impact	No impact
CPI	No impact	No impact	No impact	No impact	No impact	No impact
PR	20 min	20 min	20 min	20 min	5 min	No impact
How much (Excess returns are expressed in percentage points. Reported coefficients are adjusted to the fact that volume is expressed in logarithms and the explanatory variable is a dummy.)						
	IR		FX		Ibovespa	
	Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
COPOM	0.61	No impact	1.77	0.58	2.29	0.86
IPCA	1.19	1.14	2.00	1.93	0.95	0.63
PIM	1.21	1.30	1.76	1.76	0.19	0.86
FOMC	0.54	0.13	0.31	0.36	No impact	No impact
CPI	No impact	No impact	No impact	No impact	No impact	No impact
PR	0.41	0.43	0.39	0.44	0.31	No impact

Note: All the estimates consider a 5% level of significance.

1.5.3.Robustness to changes in the monetary surprise

I proceed by outlining that the use of longer term bonds as a proxy for the monetary surprise is justified by the fact that FOMC releases reveals more than the prime rate and give hints on the future decision which impacts the term structure of interest rates, even at the zero-bound. However, this is far from obvious, since using daily changes in longer term bonds imply additional assumptions concerning time-varying risk premiums and additional factors driving

rates other than the FOMC announcements. The best way to assess robustness is by changing the baseline contract and to analyze changes in the results.

Our reference scenario bases its monetary surprise in a long-term treasury bond, with 10 years to maturity. If, instead, we take a medium-term contract, for instance, 2 years to maturity, there are no changes in the impact signals and only one change in our persistence indicator: the impact of a 25 basis points' FOMC surprise at the FX market , in the expansion period, is faster (15 minutes as opposed to 20 minutes). If we change of the contract to a shorter one, with 1 year to maturity, FOMC's surprise impact on Ibovespa market vanishes at the expansion period. We can state that the use of a shorter term contract implies a lesser impact on Brazilian futures markets. In contrast, when we use a longer maturity contract in the domestic surprise calculus, a 1-year SWAP contract, COPOM surprises displays higher point estimate reactions when returns are taken as the dependent variable. In the expansion period, for instance, stock markets are positively related to a 25 basis points COPOM monetary surprise, raising returns by 0.25%. In general, thus, it is fair to say that the use of longer maturities amplify the impact of the monetary surprise.

In terms of volume, the change in monetary surprises' definition does not alter the results. Apart from minor changes in the intensity coefficients, COPOM's influence on volume is more pronounced in the IR market while FOMC's is in the Ibovespa one. COPOM preserves its impact on spreads over all markets, while the use of a shorter term contract do not change the fact that FOMC has no impact on the IR market trading volume.

1.5.4. Application: Out-of-sample performance based on an announcement-timing strategy

To provide a sense of the practical application of the returns' model, we describe an approach for measuring the potential gains associated with the methodology described in Section 1.4. The interpretation of the returns' impact for each announcement provides the tools to devise a simple strategy where one takes a portfolio position immediately after the announcement is public, i.e., as soon as its surprise is known. In this framework, investors take a long or short position depending on the combination between sign impact and surprise direction, as shown in the table below.

We restrain our analysis to the expansion period as we believe markets were better behaved away from the extreme events of the last quarter of 2008 and the first quarter of 2009, leading to more stable and structural estimates. We separate 80% of the observations for the in-sample estimates, shown in the table below, and the remaining 20% for the out-of-sample exercise. We also define persistent announcement as those with significant aggregate coefficients up to twenty minutes after announcement's releases. The exceptions to the persistency rule are the estimated impact of COPOM and IPCA on the IR market whose aggregation window has been reduced to ten minutes providing that such announcements are publicly available while markets are closed leading to differential informational absorption as Table 6 displays.

Table 9: In-sample estimates of the persistent impact based on regression results for each market and announcement in the expansion period
(Reported coefficients are expressed in percentage points for a unit shock. A unit shock from COPOM and FOMC: 25 basis points; IPCA and CPI: 0.10 p.p.; PIM: 1.0 p.p.; PR: 100,000 jobs.)

	IR	FX	Ibovespa
COPOM	-0.078	No impact	0.059
IPCA	0.033	No impact	No impact
PIM	No impact	No impact	No impact
FOMC	No impact	0.149	-0.224
CPI	No impact	No impact	No position
PR	No impact	No impact	0.042

The results in Table 9 generate the following high frequency trading strategy, as in Table 10. In order to take advantage of the information contained in macroeconomic announcements, investors should trade immediately after identifying its surprise component and revert to a neutral position shortly after. Note that the investment holding period varies according to the previous persistency definition (ten minutes for investments in the IR market after COPOM and IPCA announcements and twenty minutes for the remaining ones).

Table 10: Summary of the announcement-timing strategy based on regression results

	IR	FX	Ibovespa
COPOM	Sell, if surprise is positive. Buy, otherwise.	No position	Buy, if surprise is positive. Sell, otherwise.
IPCA	Buy, if surprise is positive. Sell, otherwise.	No position	No position
PIM	No position	No position	No position
FOMC	No position	Buy, if surprise is positive. Sell, otherwise	Sell, if surprise is positive. Buy, otherwise.
CPI	No position	No position	No position
PR	No position	No position	Buy, if surprise is positive. Sell, otherwise

The above strategy will be tested in 23 announcement releases from October 2010 to January 2011, a 4-month period. Transactions costs, including registration and exchange fees, are taken directly from BVMF which offers special conditions for investors registered as high frequency traders. It adopts a pricing model of differentiated and decreasing fees based on the volume executed by investors. Our results can be labeled conservative since the worst case scenario will be applied, that is, the one of highest proportional fees compatible with the initial investment proposed.

As we will see, the out-of-sample results of this strategy are encouraging. In Table 11, the consolidated results are summarized considering a USD 5 million initial investment in the FX market, and BRL 5 million in the IR and Ibovespa markets. It is clear that the consolidated results are positive for all announcements, except for investments in the Ibovespa futures market after COPOM interest rate decisions. It turns out that 16 out of 23 recommended positions generate positive returns, resulting in a 70% success rate. Note, however, that performance across announcements is not homogenous. While all FOMC-related positions

matched the anticipated market directions for all markets, COPOM influence specifically on the stock market shows the lowest success rate, with 1 positive return out of 3 announcements.

Table 11: Results of the strategies based on regression results, in nominal terms and in percentage points.

	IR (in Brazilian reais)	FX (in US dollars)	Ibovespa (in Brazilian reais)
COPOM	R$ 5.281,24		-R$ 6.500,91
IPCA	R$ 2.197,64		
PIM			
FOMC		$ 12.435,64	R$ 13.834,84
CPI			
PR			R$ 5.835,10
Total	R$ 7.478,88	$ 12.435,64	R$ 13.105,01
Excess return as a percentage of the initial investment	0.15%	0.25%	0.26%

1.6.Conclusion

This paper explores the role of macroeconomic announcements in the Brazilian futures market in order to assess the link between economic fundamentals and asset pricing. Although it has been the subject of many empirical studies, the issue is far from resolved. With a few exceptions, event studies using daily data found little evidence of this connection. The main issue is that returns are affected by a number of factors that are not easily identifiable in low frequency. Intraday data allowed us to separate the effect of announcements properly and we are able to find robust evidence of this impact in specific announcements and states of the economy.

This study contributes to the literature on the impact of macroeconomic announcements in emerging markets. Testing six announcements over the period between October 2008 and January 2011, we find that external monetary policy (FOMC) is not only the main factor driving returns in the FX market but also the single persistent one, where a 25 basis points' surprise raises FX returns in 0.191 p.p. and 0.089 p.p. in the full sample and expansion period, respectively, twenty minutes after its release. A more widespread reaction to macroeconomic announcements is observed in the Ibovespa futures market. A negative association between FOMC surprises and stock returns has been identified implying that a US monetary policy easing is related to positive stock returns in Brazil. In contrast, non-farm payroll records are positively associated with domestic stock index returns suggesting that the dividend effect is higher than the cost of capital one and also that real economy shocks are correlated between Brazilian and US economies. PR is persistent up to twenty minutes at both sample periods, when a 100,000 jobs' surprise increase returns in the stock market by 0.151 p.p. and 0.182 in the full sample and expansion period, respectively. In the IR market, we find a negative correlation between COPOM surprises and returns that can be credited to the misalignment between financial market and central bank expectations over inflation. IPCA surprises, exactly as anticipated by theory, are positively related to futures interest rates.

We also offer a practical application of the study by constructing an announcement-timing investment strategy, where investors take a long or short position depending on the combination between sign impact and surprise direction. This approach enables us to directly assess the potential gains associated to our methodological framework. As a matter of fact, it showed promising results in an out-of-sample study as we are able to correctly anticipate the direction of the returns, conditional on the surprise's signal, in 70% of the cases. State dependency is found to be a potential factor driving market returns by changing the magnitude of the coefficients that

measure the impact of announcements, occasionally eliminating predicted impacts as implied by the non-significance of estimates for the IPCA announcement in the full sample which is in contrast to the persistent results that holds in the expansion period.

Overall, our results point to large differences in the relative weight of domestic and external announcements. In Andersen et al (2007), for instance, domestic events (in this case, taking US as domestic country) play a central role in asset pricing. In our study, domestic dominance is restricted the IR market while external announcements govern price changes in the FX and Ibovespa futures markets. It is somewhat surprising, though, that the domestic real economy announcement (PIM) has negligible effect on returns. In theory, the level of information content of a data release is proportional to the effect on the financial market, triggering portfolio reallocation and influencing asset pricing. In this particular case, financial market probably faces data issues that prevent it from correctly interpreting and resolving uncertainty in the post-announcement release period. Enhancing economic data availability could be a good start in order to handle this problem.

Similarly, we contribute to the literature by finding that announcements are followed by greater trading volume, suggesting that uncertainty resolution triggers transactions in all markets irrespective of the business cycle. More important, contrary to price reaction, the effect on trading volume is widespread, showing that the absence of price reaction is not a sufficient condition to overrule the announcement importance. We also document large differences in the relative magnitude of trading volume reactions attributing it to differential levels of informational content between announcements. We finally find that bid-ask spreads often quickly revert when external announcements are released that, form a microstructure viewpoint, can indicate the prevalence of different kinds of investors and trading phases.

Finally, we show that the impact of IPCA announcements in the IR market returns vary according to the sample period. In contrast to full sample results, point estimates are significant when database is restricted to the expansion cycle. In this regard, previous theoretical work (Blanchard (1981), Veronesi (1999)) showed that asset price response to news is state-dependent, suggesting that the context may define the way financial markets process information. Due to data availability, though, state-dependency could not be properly assessed. Further research can bring light to this issue as long as one is able to split sub-samples according to the economic cycle. There are other open questions that can orient future research. In particular, the investigation of correlation across markets could indicate common factors that make them move together. The impact on volatility is another important issue that comes up naturally.

1.7.Annex A

Figure 1. Framework for the database construction

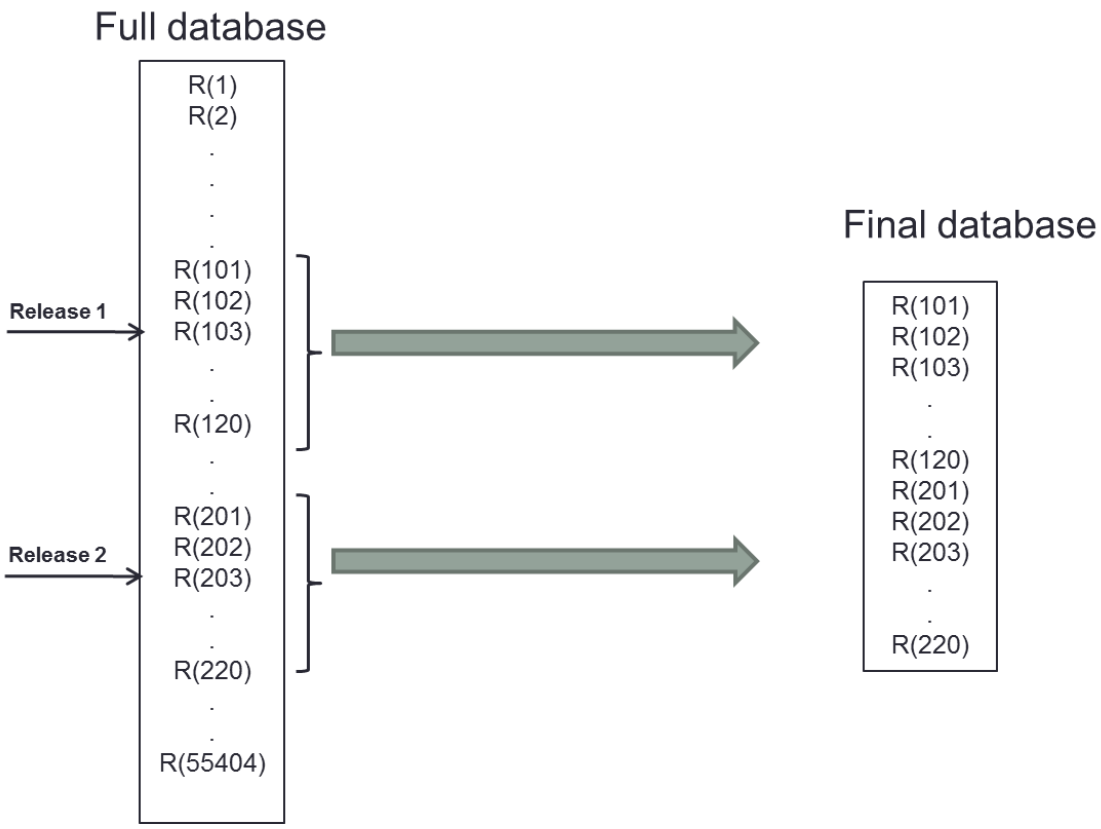


Table 12: Hourly average trading volume (number of traded contracts) and spread per futures market

	Spread			Trading Volume		
	IR	FX	Ibovespa	IR	FX	Ibovespa
1st hour	0.00176	0.16118	0.08254	1461	2406	365
2nd hour	0.00141	0.00181	0.00064	1122	2768	602
3rd hour	0.00136	0.00067	0.00061	1089	3120	657
4th hour	0.00135	0.00128	0.00059	828	2701	507
5th hour	0.00137	0.00140	0.00057	275	1552	364
6th hour	0.00135	0.00101	0.00057	675	1822	392
7th hour	0.00124	0.00057	0.00057	1345	2977	473
8th hour	0.00175	0.00166	0.00060	497	1914	498
9th hour	0.00122	0.01683	0.00066	496	1392	515

Table 13: Regression results for returns

The table shows WLS estimation's results for models (1.4.1) and (1.4.2), one for each futures market and sample period. The coefficients and t-stats are reported. Surprises are normalized according to (1.3.2.1).

		IR		FX		Ibovespa	
		Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
IR Return (t-1)	point estimate	-0.04600	-0.07780**	0.02340	0.02570	-0.07900**	0.00013
	standard deviation	(0.02860)	(0.03240)	(0.02170)	(0.02210)	(0.03140)	(0.03880)
FX Return (t-1)	point estimate	-0.01080	-0.01340	0.02220	0.01120	-0.07940**	0.23000**
	standard deviation	(0.01590)	(0.01890)	(0.02860)	(0.03010)	(0.03350)	(0.04720)
Ibovespa Return (t-1)	point estimate	-0.00842	-0.00108	-0.00025	-0.01910	-0.01850	0.05610
	standard deviation	(0.00950)	(0.01280)	(0.01380)	(0.01620)	(0.02860)	(0.03800)
COPOM surprise (t)	point estimate	-0.00055***	-	-0.00024***	-	0.00067***	0.00061***
	standard deviation	(0.00018)	(0.00018)	(0.0009)	(0.00008)	(0.00015)	(0.00015)
COPOM surprise (t-1)	point estimate	-0.00001	0.00006	0.00023**	0.00032***	-0.00037*	-0.00014
	standard deviation	(0.00018)	(0.00018)	(0.00011)	(0.00009)	(0.00019)	(0.00018)
COPOM surprise (t-2)	point estimate	0.00002	0.00004	-0.00007	0.00001	0.00011	-0.00005
	standard deviation	(0.00020)	(0.00019)	(0.00014)	(0.00009)	(0.00020)	(0.00018)
COPOM surprise (t-3)	point estimate	0.00009	0.00027	-0.00028**	-0.00015*	0.00035	0.00057***
	standard deviation	(0.00023)	(0.00022)	(0.00014)	(0.00009)	(0.00023)	(0.00019)
IPCA surprise (t)	point estimate	0.00017	0.00044***	0.00033**	0.00015	-0.00018	0.00020
	standard deviation	(0.00014)	(0.00014)	(0.00013)	(0.00012)	(0.00018)	(0.00025)
IPCA surprise (t-1)	point estimate	0.00001	-0.00016	-0.00018	-0.00006	-0.00010	-0.00001
	standard deviation	(0.00018)	(0.00017)	(0.00017)	(0.00012)	(0.00023)	(0.00025)
IPCA surprise (t-2)	point estimate	0.00025	0.00017	-0.00009	-0.00014	0.00016	0.00027
	standard deviation	(0.00019)	(0.00016)	(0.00017)	(0.00012)	(0.00021)	(0.00022)
IPCA surprise (t-3)	point estimate	-0.00017	-0.00014	0.00021	0.00014	-0.00017*	-0.00006
	standard deviation	(0.00018)	(0.00016)	(0.00017)	(0.00011)	(0.00023)	(0.00023)
PIM surprise (t)	point estimate	-0.00014	-0.00014	0.00008	0.00014	0.00017	0.00034***
	standard deviation	(0.00011)	(0.00010)	(0.00011)	(0.00009)	(0.00010)	(0.00012)
PIM	point estimate	0.00011	-0.00013	-0.00012	-0.00002	-0.00017	-0.00024*

surprise (t-1)	standard deviation	(0.00014)	(0.00014)	(0.00012)	(0.00009)	(0.00011)	(0.00015)
PIM	point estimate	0.00002	-0.00001	0.00004	0.00002	-0.00011	-0.00002
surprise (t-2)	standard deviation	(0.00017)	(0.00015)	(0.00012)	(0.00009)	(0.00013)	(0.00013)
PIM	point estimate	-0.00006	-0.00007	-0.00009	-0.00008	0.00017	0.00022*
surprise (t-3)	standard deviation	(0.00015)	(0.00013)	(0.00011)	(0.00009)	(0.00012)	(0.00012)
FOMC	point estimate	0.00017*	0.00018*	0.00079***	0.00061***	-0.00084***	-
surprise (t)	standard deviation	(0.00009)	(0.00009)	(0.00012)	(0.00010)	(0.00018)	(0.00019)
FOMC	point estimate	0.00005	-0.00003	0.00028	0.00030***	-0.00074**	-
surprise (t-1)	standard deviation	(0.00011)	(0.00009)	(0.00020)	(0.00011)	(0.00030)	(0.00015)
FOMC	point estimate	-0.00014	-0.00021**	0.00001	0.00001	-0.00017	0.00006
surprise (t-2)	standard deviation	(0.00013)	(0.00010)	(0.00019)	(0.00012)	(0.00034)	(0.00021)
FOMC	point estimate	0.00002	-0.00003	0.00007	-0.00008	-0.00022	-0.00018
surprise (t-3)	standard deviation	(0.00013)	(0.00009)	(0.00020)	(0.00013)	(0.00034)	(0.00021)
CPI	point estimate	-0.00004	-0.00002	0.00007	0.00001	-0.00007	0.00003
surprise (t)	standard deviation	(0.00008)	(0.00013)	(0.00010)	(0.00013)	(0.00016)	(0.00022)
CPI	point estimate	-0.00015	-0.00024*	0.00001	-0.00004	0.00028*	0.00040***
surprise (t-1)	standard deviation	(0.00009)	(0.00014)	(0.00011)	(0.00012)	(0.00015)	(0.00020)
CPI	point estimate	0.00011	-0.00007	0.00017*	0.00035***	-0.00035**	-0.00016
surprise (t-2)	standard deviation	(0.00010)	(0.00014)	(0.00009)	(0.00012)	(0.00016)	(0.00021)
CPI	point estimate	0.00007	0.00006	-0.00006	-0.00001	0.00008	0.00003
surprise (t-3)	standard deviation	(0.00009)	(0.00012)	(0.00010)	(0.00010)	(0.00015)	(0.00019)
PR	point estimate	0.00030***	0.00027**	-0.00042***	-	0.00096***	0.00118***
surprise (t)	standard deviation	(0.00013)	(0.00012)	(0.00016)	(0.00014)	(0.00032)	(0.00033)
PR	point estimate	-0.00010	-0.00013	0.00043*	0.00047**	0.00008	0.00020
surprise (t-1)	standard deviation	(0.00015)	(0.00013)	(0.00022)	(0.00019)	(0.00038)	(0.00041)
PR	point estimate	0.00006	0.00004	0.00005	0.00004	-0.00001	-0.00001
surprise (t-2)	standard deviation	(0.00014)	(0.00014)	(0.00022)	(0.00019)	(0.00038)	(0.00042)
PR	point estimate	-0.00013	-0.00011	0.00007	0.00011	0.00039	0.00035
surprise (t-3)	standard deviation	(0.00014)	(0.00013)	(0.00023)	(0.00020)	(0.00037)	(0.00039)
Intercept	point estimate	-0.00001	-0.00001	-0.00003***	-	0.00004***	0.00025***
	standard deviation	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00001)
Observations		2,482	1,788	2,482	1,788	2,482	1,788
R-squared		0.015	0.030	0.037	0.060	0.038	0.080

Note: standard errors in brackets. * Significance at 90% levels. ** Significance at 95% levels. *** Significance at 99% levels.

Table 14: Regression results for trading volume

The table shows WLS estimation's results for models (1.4.3) and (1.4.4), one for each futures market and sample period, where. Variable X refers to trading volume. The coefficients and t-stats are reported.

		IR		FX		Ibovespa	
		Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
IR Volume (t-1)	point estimate	0.104***	0.106***	0.007	0.012	0.008	0.014
	standard deviation	(0.022)	(0.026)	(0.013)	(0.016)	(0.009)	(0.011)
FX Volume (t-1)	point estimate	-0.025	0.003	0.236***	0.225***	0.015	0.021
	standard deviation	(0.030)	(0.033)	(0.025)	(0.029)	(0.014)	(0.016)
Ibovespa Volume (t-1)	point estimate	0.036	0.030	0.011	0.017	0.278***	0.279***
	standard deviation	(0.042)	(0.045)	(0.028)	(0.031)	(0.022)	(0.025)
COPOM dummy (t)	point estimate	1.137***	1.268***	0.463**	0.784***	0.249**	0.384***
	standard deviation	(0.245)	(0.278)	(0.199)	(0.236)	(0.125)	(0.151)
COPOM dummy (t-1)	point estimate	0.909***	0.816***	0.034	0.126	0.025	-0.069
	standard deviation	(0.247)	(0.282)	(0.190)	(0.233)	(0.125)	(0.153)
COPOM dummy (t-2)	point estimate	0.955***	1.477***	0.156	0.358	-0.019	-0.103
	standard deviation	(0.246)	(0.284)	(0.179)	(0.222)	(0.123)	(0.149)
COPOM dummy (t-3)	point estimate	0.343	0.361	0.298	0.340	0.005	0.086
	standard deviation	(0.243)	(0.279)	(0.189)	(0.231)	(0.125)	(0.154)
IPCA dummy (t)	point estimate	0.881***	1.086***	0.116	0.197	-0.191*	-0.228*
	standard deviation	(0.237)	(0.255)	(0.166)	(0.183)	(0.101)	(0.115)
IPCA dummy (t-1)	point estimate	0.246	0.176	0.247	0.140	0.213**	0.196*
	standard deviation	(0.247)	(0.269)	(0.153)	(0.171)	(0.104)	(0.118)
IPCA dummy (t-2)	point estimate	0.404	0.135	-0.077	-0.041	-0.250**	-0.215*
	standard deviation	(0.231)	(0.245)	(0.153)	(0.173)	(0.100)	(0.113)
IPCA dummy (t-3)	point estimate	0.518	0.246	-0.188	-0.241	-0.038	-0.054
	standard deviation	(0.227)	(0.237)	(0.157)	(0.177)	(0.099)	(0.114)
PIM dummy (t)	point estimate	0.407*	0.533**	0.615***	0.869***	-0.020	0.006
	standard deviation	(0.224)	(0.244)	(0.160)	(0.185)	(0.096)	(0.111)
PIM dummy (t-1)	point estimate	0.142	0.096	0.113	0.076	0.055	0.052
	standard deviation	(0.228)	(0.250)	(0.162)	(0.192)	(0.095)	(0.110)
PIM	point estimate	0.283	0.262	0.169	0.157	-0.106	-0.188*

dummy (t-2)	standard deviation	(0.218)	(0.234)	(0.149)	(0.169)	(0.095)	(0.109)
PIM	point estimate	0.154	0.224	0.175	0.289*	-0.042	-0.095
dummy (t-3)	standard deviation	(0.215)	(0.230)	(0.151)	(0.174)	(0.093)	(0.105)
FOMC	point estimate	-0.254	-0.178	0.584***	0.717***	0.767***	0.980***
dummy (t)	standard deviation	(0.267)	(0.293)	(0.169)	(0.183)	(0.134)	(0.155)
FOMC	point estimate	0.459*	0.489*	0.478***	0.568***	0.778***	0.746***
dummy (t-1)	standard deviation	(0.259)	(0.282)	(0.171)	(0.187)	(0.141)	(0.162)
FOMC	point estimate	-0.136	-0.098	0.181	0.240	0.234*	0.249*
dummy (t-2)	standard deviation	(0.264)	(0.287)	(0.161)	(0.175)	(0.132)	(0.151)
FOMC	point estimate	0.099	0.104	0.305*	0.359**	0.466***	0.454***
dummy (t-3)	standard deviation	(0.262)	(0.285)	(0.165)	(0.180)	(0.131)	(0.150)
CPI	point estimate	0.582**	0.744***	0.633***	0.732***	0.324***	0.321***
dummy (t)	standard deviation	(0.238)	(0.257)	(0.125)	(0.145)	(0.099)	(0.113)
CPI	point estimate	0.407*	0.357	-0.00175	0.062	-0.065	-0.093
dummy (t-1)	standard deviation	(0.239)	(0.258)	(0.131)	(0.151)	(0.098)	(0.114)
CPI	point estimate	0.069	0.127	-0.0979	-0.072	-0.190**	-0.220**
dummy (t-2)	standard deviation	(0.229)	(0.250)	(0.123)	(0.146)	(0.095)	(0.112)
CPI	point estimate	0.217	0.167	-0.0952	-0.061	-0.055	-0.028
dummy (t-3)	standard deviation	(0.223)	(0.247)	(0.123)	(0.146)	(0.093)	(0.109)
PR	point estimate	2.082***	2.468***	1.729***	1.688***	1.406***	1.619***
dummy (t)	standard deviation	(0.238)	(0.259)	(0.132)	(0.152)	(0.096)	(0.109)
PR	point estimate	0.731***	1.011***	-0.0292	0.022	0.147	0.132
dummy (t-1)	standard deviation	(0.269)	(0.303)	(0.146)	(0.172)	(0.111)	(0.126)
PR	point estimate	0.229	-0.094	0.177	0.203	0.003	0.039
dummy (t-2)	standard deviation	(0.237)	(0.258)	(0.129)	(0.149)	(0.098)	(0.112)
PR	point estimate	-0.123	-0.256	0.164	0.214	0.001	0.002
dummy (t-3)	standard deviation	(0.222)	(0.235)	(0.135)	(0.155)	(0.099)	(0.111)
Intercept	point estimate	0.759***	0.727***	0.695***	0.685***	0.661***	0.644***
	standard deviation	(0.054)	(0.059)	(0.0365)	(0.041)	((0.026)	(0.030)
Observations		2,482	1,788	2,482	1,788	2,482	1,788
R-squared		0.081	0.112	0.132	0.143	0.184	0.213

Note: standard errors in brackets. * Significance at 90% levels. ** Significance at 95% levels. *** Significance at 99% levels.

Table 15: Regression results for spreads

The table shows WLS estimation's results for models (1.4.3) and (1.4.4), one for each futures market and sample period, where. Variable X refers to bid-ask spread. The coefficients and t-stats are reported.

		IR		FX		Ibovespa	
		Full sample	Expansion period	Full sample	Expansion period	Full sample	Expansion period
IR Spread (t-1)	point estimate	0.08450***	0.06290*	0.02370	0.02610	-0.04220	-0.01230
	standard deviation	(0.02740)	(0.03130)	(0.02450)	(0.02110)	(0.03440)	(0.03360)
FX Spread (t-1)	point estimate	0.01100	0.06690***	0.05310*	0.05360*	-0.03600	-0.04190
	standard deviation	(0.01730)	(0.02470)	(0.02940)	(0.03090)	(0.02790)	(0.03240)
Ibovespa Spread (t-1)	point estimate	0.01790	0.03060	0.03930**	0.04020**	-0.00315	0.00968
	standard deviation	(0.01310)	(0.01900)	(0.01550)	(0.01580)	(0.02720)	(0.03150)
COPOM dummy (t)	point estimate	0.63300***	0.19700	1.76400***	0.62900***	1.58900***	0.40900
	standard deviation	(0.13200)	(0.20200)	(0.14700)	(0.16100)	(0.20100)	(0.25800)
COPOM dummy (t-1)	point estimate	-0.08070	-0.19500	-0.09340	-0.06530	0.19800	0.13500
	standard deviation	(0.12800)	(0.16200)	(0.17800)	(0.17700)	(0.19700)	(0.20400)
COPOM dummy (t-2)	point estimate	-0.00751	0.03480	0.00686	-0.10200	0.32500*	0.11300
	standard deviation	(0.11000)	(0.14400)	(0.17300)	(0.18800)	(0.18900)	(0.18100)
COPOM dummy (t-3)	point estimate	0.06530	0.10100	0.09650	0.11500	0.17900	0.20000
	standard deviation	(0.10200)	(0.12500)	(0.13300)	(0.13200)	(0.15800)	(0.15500)
IPCA dummy (t)	point estimate	0.71000***	0.66300***	1.88300***	1.74000***	0.88200***	0.44600***
	standard deviation	(0.10800)	(0.12000)	(0.13200)	(0.11300)	(0.19000)	(0.17300)
IPCA dummy (t-1)	point estimate	0.39700***	0.31900**	-0.02620	-0.02020	0.06450	0.05930
	standard deviation	(0.12000)	(0.13300)	(0.15500)	(0.13100)	(0.18500)	(0.16500)
IPCA dummy (t-2)	point estimate	0.07000	0.11000	0.15100	0.14400	-0.11300*	-0.08000
	standard deviation	(0.10900)	(0.12900)	(0.14700)	(0.13200)	(0.17700)	(0.15500)
IPCA dummy (t-3)	point estimate	0.01160	0.05250	-0.00654	0.06700	0.11200	0.20400
	standard deviation	(0.09490)	(0.11200)	(0.12800)	(0.11400)	(0.15100)	(0.14100)
PIM dummy (t)	point estimate	0.95300***	1.05400***	1.72000***	1.75700***	0.77500***	0.50100***
	standard deviation	(0.10600)	(0.11800)	(0.11900)	(0.10200)	(0.14100)	(0.13500)
PIM dummy (t-1)	point estimate	0.08360	0.05040	-0.05240	-0.03260	0.34000**	0.35400**
	standard deviation	(0.10700)	(0.12900)	(0.13200)	(0.11600)	(0.15400)	(0.15000)
PIM dummy (t-2)	point estimate	0.07680	0.11800	0.05990	0.04830	0.07340	-0.03250
	standard deviation	(0.09040)	(0.10400)	(0.11300)	(0.09800)	(0.14200)	(0.13100)

PIM dummy (t-3)	point estimate	0.09970	0.08130	0.03070	-0.01120	0.00371	0.04160
	standard deviation	(0.08620)	(0.09810)	(0.09680)	(0.08440)	(0.12300)	(0.11400)
FOMC dummy (t)	point estimate	0.24200**	0.13000	0.21200**	0.22100***	-0.03200	-0.05690
	standard deviation	(0.10900)	(0.12400)	(0.08580)	(0.06710)	(0.10700)	(0.09900)
FOMC dummy (t-1)	point estimate	0.27400**	0.25100**	0.13800	0.14500**	-0.08470	-0.09670
	standard deviation	(0.10700)	(0.11700)	(0.09010)	(0.07230)	(0.10700)	(0.09760)
FOMC dummy (t-2)	point estimate	-0.02500	-0.01940	-0.01280	0.00302	-0.16900*	-0.20500**
	standard deviation	(0.09810)	(0.10600)	(0.07730)	(0.05910)	(0.09360)	(0.08440)
FOMC dummy (t-3)	point estimate	0.04680	-0.05160	-0.02460	-0.00982	0.03740	0.05260
	standard deviation	(0.09330)	(0.10300)	(0.07170)	(0.05430)	(0.09190)	(0.08140)
CPI dummy (t)	point estimate	0.14000	0.08700	0.09120	0.06670	0.03610	0.01010
	standard deviation	(0.08780)	(0.10400)	(0.07540)	(0.06690)	(0.12500)	(0.11700)
CPI dummy (t-1)	point estimate	-0.03710	-0.06810	-0.00304	0.05590	0.05160	0.03830
	standard deviation	(0.08520)	(0.10000)	(0.07800)	(0.06950)	(0.11700)	(0.10700)
CPI dummy (t-2)	point estimate	0.02010	0.00590	0.00623	0.04640	0.13500	0.13400
	standard deviation	(0.07530)	(0.09020)	(0.06880)	(0.06300)	(0.10500)	(0.09960)
CPI dummy (t-3)	point estimate	0.04290	0.04080	-0.02440	0.01630	0.08900	0.07660
	standard deviation	(0.07580)	(0.09070)	(0.06520)	(0.05880)	(0.10500)	(0.09990)
PR dummy (t)	point estimate	0.41000***	0.45400***	0.22200**	0.25800***	0.31400**	0.11400
	standard deviation	(0.09050)	(0.10200)	(0.10200)	(0.08530)	(0.13500)	(0.12500)
PR dummy (t-1)	point estimate	-0.03450	-0.03120	0.06350	0.07880	-0.00728	0.00512
	standard deviation	(0.08180)	(0.09230)	(0.10400)	(0.08740)	(0.13300)	(0.12000)
PR dummy (t-2)	point estimate	-0.00839	0.03300	0.14500	0.11700	0.07540	0.02680
	standard deviation	(0.08250)	(0.09310)	(0.09270)	(0.07920)	(0.12800)	(0.11200)
PR dummy (t-3)	point estimate	0.04120	-0.02780	-0.03950	-0.01050	-0.08650	-0.11200
	standard deviation	(0.07880)	(0.08760)	(0.08280)	(0.07070)	(0.12500)	(0.11200)
Intercept	point estimate	0.84400***	0.79900***	0.83800***	0.83600***	1.03200***	1.00700***
	standard deviation	(0.03290)	(0.04100)	(0.03840)	(0.03750)	(0.04980)	(0.05300)
Observations		2,482	1,788	2,482	1,788	2,482	1,788
R-squared		0.110	0.117	0.245	0.302	0.074	0.034

Note: standard errors in brackets. * Significance at 90% levels. ** Significance at 95% levels. *** Significance at 99% levels.

2 Price Discovery in the Brazilian FX market

2.1.Introduction

The expansion of trading venues is an institutional trend that can potentially promote efficiency and enhance the spread of information. Barclay et al (2003), for instance, provide evidence of the positive effects of a secondary market to Nasdaq. Yet, according to Hendershot & Mendelson (2000), the impact of said proliferation of trading platforms on social welfare depends on the nature of the financial security in question as well as on the type of investor. As the information set under which prices are formed is the same regardless of the market under study, a natural question that arises is in which of them new information impounds changes in the price of a security, that is, in which market does price discovery takes place.

When applied to the Brazilian FX market, this concern is of particular interest in that we will be able not only to determine the dominant market (spot or futures) but also discuss the role of institutions in the price discovery process. Brazil has a long history of foreign exchange (FX) crises that gave rise to different degrees of capital controls, creating an atypical structure of its currency market where, contrary to the common practice, the futures market concentrates most part of the liquidity as documented by Ventura & Garcia (2012). The aim of this paper is to indicate which market (spot or futures) adjusts more quickly to the arrival of new information and to provide a measure of efficiency that considers the dynamic response of each market to a new equilibrium.

We use two datasets comprising high frequency prices from the spot and futures Brazilian FX market that covers the period between January 2008 and June 2013. The spot FX market database has been provided by Bloomberg while the futures one by BVMF[29], both including prices at a sampling frequency of five minutes.

The contribution of the present study to the literature is twofold. First, institutional and market instability entails a complementary analysis of sub-samples in order to check for potential differences in the results. Hence, by checking for dominance switching over each semester of the sample, it will be possible to explore the results with regard to financial indicators and policy actions. Moreover, the methodology is also applied to an emerging country with a highly regulated FX environment, broadening the scope of the research. Also, note that a Brazilian FX market investigation that applies price discovery methodology combined with high frequency data has not been yet carried out. Thus, even if previous results are validated in the light of the price discovery methodology, this represents a significant contribution to the literature.

We find that futures market dominates FX price discovery in Brazil. It accounts for 66.2% of the variation in the fundamental price shock and for 97.4% of the fundamental price composition. In a dynamic perspective, futures market is also more efficient since, when markets are subjected to a shock in the fundamental price, it is faster in recovering to equilibrium. We attribute this finding to superior levels of liquidity and transparency in this market. In fact, transaction restrictions in the spot market refrain operations from key agents, in special high frequency trading (HFT)[30] that an extensive literature treat as an important driver

[29] BVMF is the Brazilian Securities, Commodities and Futures Exchange , short for “Bolsa de Valores, Mercadorias e Futuros”.

[30] HFT refers to the use of sophisticated technological tools and computer algorithms in order to trade securities and change positions as fast as possible in face of potentially price shocks.

of price efficiency (see Brogaard et al (2013), Hasbrouck & Saar (2013)). Besides, our findings are in accordance with those of Ventura & Garcia (2012), where the same conclusions were reached through the application of an order flow approach.

We also investigated whether results are robust to sub-samples. When we break in sub-samples by semester, price discovery figures show non-trivial variations. Despite the fact that futures market dominance still holds in all sub-samples, results do not follow an easily identifiable pattern. Spot market offer-demand disequilibrium, central bank interventions and institutional investors' pressure in the futures market emerge as potential explanatory factors. We also identified a regulatory measure that restricted futures transactions as a potential price discovery driver. Finally, futures dominance in high volatility regimes provides additional evidence that prices are formed in this market and then transmitted to the spot market through arbitrage.

This paper is structured as follows. In Section 2.2, we briefly list the main references on the subject. In Section 2.3, the main figures and features of the Brazilian FX market are presented. Next, we document the data sources and discuss its potential limitations. Section 2.5 presents the empirical framework and discusses the price discovery metrics that will be used in the study. In Sections 2.6 and 2.7, the results for the whole sample and sub-samples are discussed, respectively. Finally, we offer concluding remarks in Section 2.8.

2.2.Related work

Price discovery literature takes advantage of the fact that prices are linked by arbitrage to construct a common or fundamental price in a situation where an asset is traded in more than one market. The search for an equilibrium price is not new, dating back to Schreiber & Schwartz (1986). It has been given special attention with the availability of high frequency[31] data and the development of a direct measure of price discovery in Hasbrouck (1995), the Information Share (IS), which measures the relative contribution of each market under study to the variance of the efficient price. Under the same framework, the Component Share (CS)[32], an alternative price discovery metric, has been proposed based on Gonzalo & Granger's (1995) separation between transitory and permanent components. More recently, Yan & Zivot (2010) proposed a combination of both measures to form the Information Leadership Share (ILS). The ILS is a dynamic measure of relative market efficiency, based on a structural model of Yan & Zivot (2007) that addresses two main drawbacks of the previous two measures. First of all, they are based on reduced-form representations. Second, they are static in nature.

The use of price discovery measures was initially driven by the effort to examine price leadership in fragmented markets. Hasbrouck (1995, 2003) compared IS values for assets traded domestically in US markets while Grammig, Melvin & Schlag (2005) studied three German stocks traded in US and German markets and found that price discovery happened domestically. Caporale & Girardi (2013) also revealed a special role for the domestic market in a highly fragmented environment: the euro-denominated bonds. On the other hand, Fernandes & Scherrer (2011) found evidence of the international dominance by comparing prices from Vale and Petrobras, the main companies of the Brazilian stock market, which are negotiated domestically and abroad.

Although it has been the subject of various studies in the literature, the leadership contest between futures and spot FX markets is rather unsettled. While Cabrera, Wang & Yang (2009) shown that the spot[33] market leads, Rosenberg & Traub (2009) stated that their conclusion does

[31] Daily studies are able to provide evidence on price linkages across markets, but they cannot circumvent the problem of non-synchronous closing prices.

[32] Many authors were involved in the early use of CS to measure price discovery (e.g., Booth et al (1999), Chu et al. (1999) and Harris et al. (2002).

[33] EUR/USD and JPY/USD

not hold in all periods. Chen & Gau (2010) compared IS and CS measures in sub-samples and found that the futures market gains importance surrounding macroeconomic announcements for the EUR/USD and JPY/USD. With respect to emerging markets, Boyrie, Pavlova & Parhizgari (2012) analyzed Brazilian real (BRL), Russian ruble (RUB) and South African rand (ZAR) using daily data. Whereas in Russia, the spot market dominates, in Brazil it is the futures one and the results were inconclusive about South Africa. In Brazil, there is additional evidence of the futures market dominance. Garcia & Urban (2005) accounted for the temporal precedence of futures FX prices by means of Granger causality tests. Later, Garcia & Ventura (2012) reached the same conclusion by comparing the informational content in the order flow of each market and the relative speed of adjustment of its cointegrated series.

Recent applied studies also analyzed the relationship between futures and spot prices in different markets. Schultz & Swieringa (2013), for instance, show that UK natural gas futures is the main venue for price discovery when comparing to physical trading hubs. In contrast, Muravyev et al (2013) find no economically significant price discovery in the US option market. Using a database that included 39 US stocks and options from April 2003 to October 2006, the authors conclude that stock prices are insensitive to put-call parity deviations and that option prices resolve the misalignment.

2.3.The FX market in Brazil

The Central Bank of Brazil executes the FX policy established by the National Monetary Council (CMN), which is composed by the President of the Central Bank and the Ministers of Finance[34] and Planning. It holds all the authority in determining the institutions that can directly participate in the FX market and also performs the role of regulation. Since 1999, Brazil has adopted a de facto administered floating FX regime where the Central Bank has intervened to avoid excess volatility and build FX reserves.

Spot market refers to FX contracts with a financial settlement period of up to two days and is divided into two main segments: primary and secondary. It is in the primary market where balance of payment transactions occur between resident and non-resident agents, including the public sector, with authorized financial institutions acting as intermediaries. Outflows from the primary market bifurcates into a commercial flux and a financial one. In the commercial segment, the major players are non-financial institutions with FX obligations as only importer and exporters of goods are allowed in this segment. Services and capital flows are registered in the financial segment.

Transactions in the primary market naturally affect FX balances of the financial institutions. To restore the equilibrium and reduce risk, they resort to the secondary market, also called interbank (IB) market, where transactions are mainly denominated in dollars as the external currency. The scope of operations in the IB market includes not only those to meant to satisfy the restrictions to the net positions imposed by the Central Bank but also directional ones. At last, all FX transactions, either in the primary or in the secondary market, are closed through specific contracts which are registered in a consolidated system, the *Sistema Cambio*, administered by the Central Bank. There are 189 institutions authorized to operate the FX market, 97 of which are multiple and commercial banks. In 2011, approximately 20 banks concentrated 80% of the total volume in both segments of the spot market. But Brazil is not alone in this subject. The BIS (2010) Triennial Survey on FX markets points out that the declining trend of financial institutions participating in the global interbank FX market is due to concentration in the banking industry. In the US, for instance, 20 banks were responsible for 75% of the FX turnover in 1998, while only 7 banks were responsible for the same amount in 2010. With a few exceptions, the figures for other countries show the same trend.

In the IB market, transactions can be booked over the counter (OTC) or through the Foreign Exchange Clearinghouse (BMC), operated by the Securities, Commodities and Futures

[34] Known as Economics Minister in Brazil.

Exchange company (BVMF) since the restructuring of Brazilian payments system in April 2002. The vast majority (approximately 95%) of the gross volume of the interbank spot FX market is settled through the BMC, which turned out to represent important progress in terms of risk management as transactions are, by regulatory enforcement, registered without delay. It can also take place directly between banks, through intermediaries or in the Spot Dollar Pit, the Electronic Brokering System introduced by BVMF in February/2006 in an attempt to increase transparency in the FX market. In spite of this effort, it remains clear from Table 16 that the Spot Dollar Pit is losing its relative importance over time and the vast majority of operations are spread among various dealers, some of them even providing access to proprietary electronic systems to facilitate and concentrate operations. This kind of trade brings its inconveniences in that prices are not publicly and instantaneously known. Fragmentation is not a weakness in itself as it can be an important driver of efficiency gains by fomenting the competition between brokers. But fragmentation should not come at the expense of transparency, as it seems to be the case. Electronic transactions play a very important role accounting for approximately 55% of the total IB market turnover worldwide, according to same BIS (2013) Triennial Survey.

The derivatives market, in turn, performs operations of longer maturity aimed at transferring risk between investors. Whereas forwards are usually traded OTC, futures contracts are highly standardized, publicly traded on organized exchanges and cleared through a clearing house[35]. Trading is facilitated by the use of identical contracts and margin requirements as well as counterparty risk are reduced by the netting of long and short positions. For this reason, futures prices will be the reference for the prevailing price in the derivatives market. As the transactions are referenced in dollars but settlement is in domestic currency, they are not as restricted as the spot market, including also non-financial institutions, external investors and individuals. The access of different participants generates more liquidity and market depth[36], making the impact of transactions less pronounced in the futures than in the spot. The result is greater trading volume and market liquidity which, in turn, potentially improves information transmission of relevant market information to market prices. According to Table 16, from 2006 to 2012, the proportion of trades in the futures market relative to the IB market increased from five to nine, i.e., for each dollar traded at the IB market, nine dollars were traded in the form of futures contracts.

Table 16 – Total trading volume in each market per year (in billion dollars)

	IB Spot market		Futures market
	Spot Dollar Pit	Total	
2006	55.4 (11.8%)	471.4	2315.2
2007	123.4 (15,0%)	822.1	4235.2
2008	122.5 (16,8%)	730.5	4370.0
2009	152.4 (26,1%)	582.9	3338.8
2010	57.4 (8,6%)	668.4	4122.7
2011	66.6 (13,0%)	512.4	4308.4
2012	28.7 (6,1%)	467.5	4202.5

Source: Central Bank of Brazil and BVMF
Note: In parenthesis the share of BVMF Market relative to the IB market

[35] In Brazil, BVMF and its clearing house concentrates all FX futures contracts.

[36] Ventura & Garcia concluded that the impact of transactions in the futures market is smaller than in the spot one.

However, in Brazil, the futures market assumes a much broader role, more than it was primarily designed to. Due to regulatory restrictions, some operations that should be done in the spot market are synthetically reproduced in the futures one, as Garcia & Urban (2005) described[37]. This evidence becomes clear when we find that futures concentrates over 90% of its volume on the first to mature contract, with maturity of one month or less. Taking this into consideration, it is fair to say that the Brazilian FX market has an unusual configuration as opposed to central FX markets in which the spot concentrates liquidity and the futures preserves its role in long term transactions.

The main argument in favor of futures market dominance is that prices are formed in the most liquid market and then transmitted via arbitrage to the less liquid one, futures and spot respectively in the Brazilian case. When a bank must offset a position originated by a transaction in the primary market, it may and generally prefers to resort to the futures market. Accordingly, private information via order flow from the primary market is directed to the futures market, not to the spot one. Whereas this practice creates simplicity, it also generates an interest rate risk due to the misalignment between spot and futures positions making it necessary to transfer positions along the day. The constant demand for this operation motivated the emergence of a specific market: the “casado”. Under this OTC contract, an instantaneous forward premium is traded allowing both markets to be linked. One of the hypotheses tested here is the one of futures market dominance.

2.4.Database

Our database consists of regularly-spaced data on futures and spot market prices between January 2008 and June 2013, or 1346 trading days. As far as futures transaction prices are concerned, we can say that the whole market is contemplated in that all relevant operations are necessarily done at BVMF, our data source, with the support of its clearinghouse. However, spot market transactions are spread among various dealers and the spot price traded at the Spot Dollar Pit corresponds to no more than 10% of the total IB market in the sampling period. Actually, FX spot market decentralization represents a challenge in terms of data collection, but Bloomberg provides a good indication, named Bloomberg BGN, which is a simple average price including both indicative prices or executed ones from various sources.

Hasbrouck (1995) proposes to use the highest possible frequency in order to reduce correlation between VECM residuals. At the same time, to the microstructure issues usually found in high frequency studies, we must add that microstructure noise in the spot market is a mixture of different noises, originated in each data supplier’s transaction environment. In this scenario, high frequency data can give light to a noise structure that we cannot assess without additional information making it reasonable to consider a five-minute frequency, which is the higher one at our disposal for the spot market[38], as our reference case and further decrease the frequency to ten and thirty minutes to assess the robustness of the results.

We are under what Hasbrouck (2002) calls data thinning where a market that posts frequently is forced to follow the pattern of the less frequent one. Indeed, handling data from multiple sources and with different trading frequencies requires assumptions that are not innocuous when it comes to price discovery analysis. Specifically, we had to define price intervals according to the less liquid market as the data on FX futures prices are more frequent. As Hasbrouck (2002) points out, to obtain a multivariate series, prices are adjusted[39] to

[37] Due to liquidity constraints in the spot market, banks usually prefer to perform FX transactions in the futures market. During the day, they are able to transmit by means of synthetic operations that match positions between the markets (for instance, “casado” or “diferencial”. For details, see Garcia and Urban (2004). It is also true that price disequilibrium is not the only factor triggering “casado” transactions. Spot and hedging demands and BCB interventions are additional factors that must be taken into account.

[38] We had futures market prices for every one minute interval.

[39] To obtain a regularly-spaced series, prices are supposed to be equal between each transaction.

guarantee synchronization and determined more or less contemporaneously. Thinning the data reduces the information set, just like any censoring procedure. Thus, how can IS be misleading when trading frequencies differ? Suppose, for instance, that the satellite market only trades after the dominant market settles down in reaction to the arrival of new information. In that case, trading is endogenous to the information process and the informational leadership can be obscured by data frequency.

Evidence provided by FX traders indicates that the transfer between futures and spot positions is not a continuous process. “Casado” transactions are concentrated in the morning due to higher demand from corporate customers and to the formation of “Ptax”[40]. They are also positively related to trading volume and, as a result, negatively related to volatility. Due to the microstructure considerations, we cannot rule out the “thinning the data” effect thus introducing an element of doubt that will only be elucidated as far as the above data frequency collection issues are solved.

The BVMF futures market opens at 09:00 AM and remains active until 06:00 PM (local time) and the most liquid contract is always the one with maturity date in the first day of the next month. Two days before expiring, we switch to the one maturing in the following month. The opening hour of Bloomberg spot market prices is the same, but the closing time varies along the database period. As such, the joint database will consider only the periods in which both markets are open totaling 140,153 five-minute observations. Also, price discovery measures do not include the overnight return and are estimated only during the daily continuous trading sessions.

In light of the no-arbitrage condition, they share a relationship that is a function of domestic and foreign interest rates, known as covered interest rate parity (CIP). This condition assumes that investing in a risk-free asset in US is equivalent to invest the same amount in Brazilian market protecting from FX variation in the futures market. But Brazil has both a history of defaults and a non-convertible currency, which causes a divergence between the two types of investment in terms of risk, which in turn explains recurrent CIP violations. “Cupom cambial” is the interest rate in dollars for an investment in Brazil and is traded as a futures contract at BVMF. Taking country risk[41] into account, “cupom cambial” allows the relationship between futures and spot prices to take the following form:

$$F_t = S_t . e^{(i_t - i_t^*)(T-t)} \qquad (2.4.1)$$

Where F_t is the futures price, S_t is the spot one, i_t^* is the “cupom cambial”, i_t is the domestic interest rate for the same maturity and (T-t) the remaining time to maturity.[42]

Although the underlying asset for the futures contract is the spot one and, hence, they share a common price, its relationship includes time-variant variables that are incompatible with a linear cointegration structure which is the baseline for the “one security, many markets” approach. Before calculating price discovery measures, we must correct the futures price according to (2.4.1) for every five-minute observation. Due to data availability, we will perform this correction with two approximations. The first one is related to the fact that we do not possess intraday data on both interest rates and we will approximate it by the daily data assuming that the correction factor is rather insensitive to small changes in interest rates. Also, the interest rate values should be taken from each term structure observing the futures contract’s maturity. This is true for “Cupom Cambial” futures data that exactly matches the dollar futures one. On the other hand, since short-term interest rate futures have low liquidity parameters, the 30-day interest rate swap is the best choice as negligible differences are expected in terms of risk premium.

[40] "Ptax" is Brazil’s benchmark rate that is used to settle currency futures contracts, among other things.

[41] See Didier, Garcia & Urban (2003), for an exposure of the determinants of FX and country risk.

[42] Cupom cambial is expressed in calendar days while domestic interest rates, in business days.

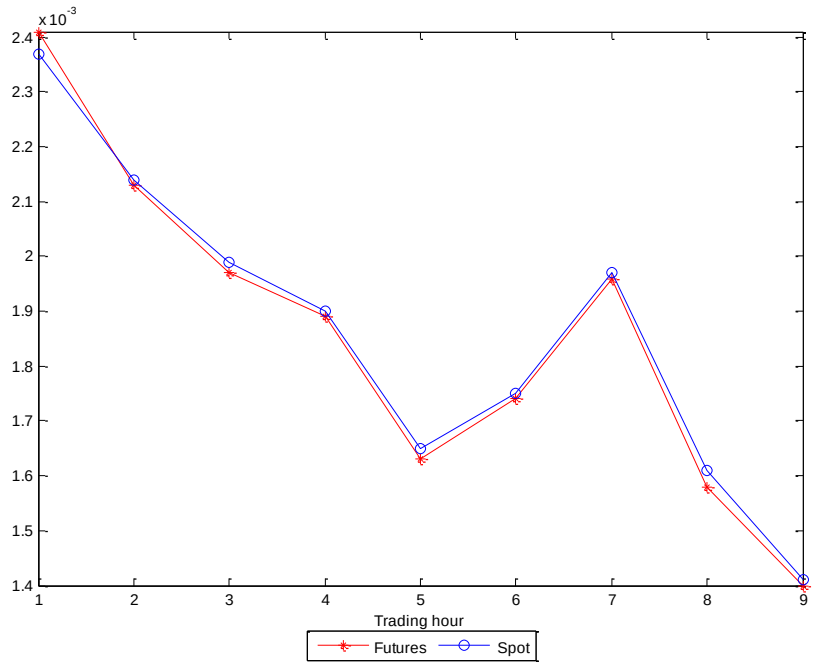
Table 17 shows that while average futures prices are superior, the comparison between daily average standard deviation suggests a close pattern. In fact, futures and spot prices are highly correlated in daily frequency and the first converge downward to meet the latter in the last day of the contract, a situation described as contango. As often reported for high-frequency data, there is some evidence of negative serial correlation for low lags in both five-minute returns, possibly due to microstructure effects[43], but higher lags have no signification correlations.

Table 17: Descriptive statistics for futures and spot prices between January 2008 and June 2013

	Spot	Futures
Five-minute mean	1.865	1.871
Daily average of five-minute standard deviation	0.0064	0.0065
First-order serial autocorrelation returns	-0.015	-0.025

From Graph 5, it is clear that both return series display similar intraday volatility patterns. In the beginning of the trading day, volatility reaches its peak and slowly decreases until the 5th trading hour, what corresponds to end of lunch time in Brazil. In the following two trading hours, volatility increases possibly linked to market activity peak in the U.S. financial centers and, finally, there is another decline in the end of the day.

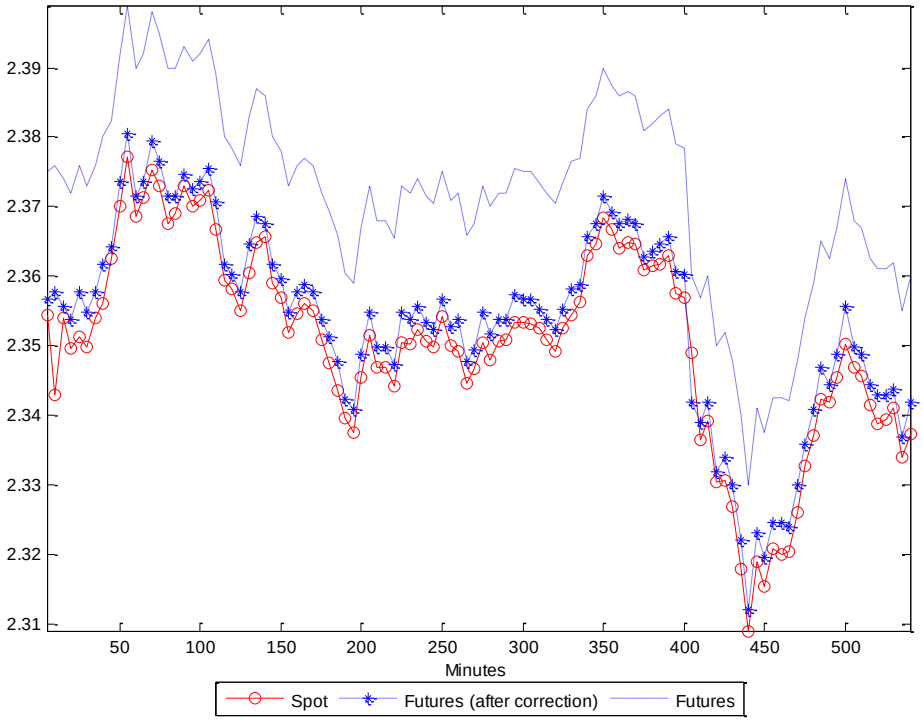
Graph 5: Daily average of five-minute standard deviation prices per trading hour



We have already discussed factors that affect the microstructure of each market which translates not only in deep differences in terms of liquidity but also can affect the relative efficiency of the markets. Indeed, this joint movement still holds when we increase the sampling frequency, but price divergences may be present in some moments depending on the each market´s speed of adjustment to new information, as Graph 6 shows.

[43] According to microstructure theory, the use of mid-spreads instead of transactions prices could minimize negative serial correlation.

Graph 6: Futures and spot daily intraday five-minute prices at 1st December, 2008



2.5.Methodology

Although the seminal paper from Hasbrouck (1995) has raised a series of developments over the recent years, all of them departed from the same principle: the identification of the efficient or fundamental price, common to all the markets where the asset is traded. According to this notion, prices for the same asset can deviate from one another in the short run due to trading frictions, but both are connected to its fundamental value and will ultimately converge in the long run. Consider that an asset trades on two venues with potentially different prices (p_{1t},p_{2t}). Since securities are identical, they must share a fundamental price m_t which, by assumption, follow a random walk process as follows:

$$m_t = \lim_{\tau \to \infty} E\left[p_{i,t+\tau}/I_t\right]$$

$$\mu_t = m_t - m_{t-1}$$

$$E[\mu_t] = E[\mu_t . \mu_s] = 0, \forall\, s \neq t \qquad (2.5.1)$$

Where I_t denotes the information available at time t and index i refers to each trading venue.

Price differences are assumed to be transitory and covariance stationary, arising from the fact that securities are subjected to different sources of microstructure noise such as bid-ask bounce and discreteness of price changes, all of them summarized in variable s_{it}. Thus, prices are defined as the sum of a permanent and a transitory component as suggested by Stock & Watson (1988) in its common stochastic trend representation:

$$p_t = \begin{pmatrix} p_{1t} \\ p_{2t} \end{pmatrix} = \begin{pmatrix} m_t \\ m_t \end{pmatrix} + \begin{pmatrix} s_{1t} \\ s_{2t} \end{pmatrix} \qquad (2.5.2)$$

$$E\left(\lim_{\tau\to\infty}(s_{i,t+\tau}/I_t\right) = 0$$

On these assumptions, prices are integrated of order one (I(1)) and there exists a VMA (Vector Moving-Average) representation as follows:

$$\Delta p_t = \Psi(L)e_t \tag{2.5.3}$$

Where $p_t=(p_{1t},p_{2t})$ is a 2x1 column vector of prices and Δp_t, its first difference.

Despite the fact that prices are non-stationary, the first difference is stationary, i.e., β=(1 ; -1) is a cointegration vector up to a scale factor. Defining Ψ(1) as the sum of all VMA coefficients or long-run impact matrix, the value of β implies not only that β'*Ψ(1)=0 but also that the rows of Ψ(1) are identical. Denoting ψ as the common row, Beveridge & Nelson (BN) decomposition yields the following representations in terms of price levels:

$$\Psi(L) = \Psi(1) + (1-L)\Psi^*(L)$$

$$p_t = p_0 + \psi(\textstyle\sum_{s=1}^{t} e_s)\iota + \Psi^*(L)e_t \tag{2.5.4}$$

The first term is a vector of initial value that represents non-stochastic differences between prices (average spread, for instance). The middle term is the efficient or common price that we wish to estimate and the last term accounts for the zero mean residuals, both equivalents to m_t and s_{it} in equation (2.5.2).

From (2.5.4), the common row ψ is a 1x2 vector that can be interpreted as the proportion of each market's contemporaneous shock that is incorporated into the efficient price. Then, how can we recover the value of ψ? We refer to Hamilton (1994) dynamic programming so as to identify the VMA parameters (2.5.3) from the estimation of the following Vector Error Correction Model (VECM):

$$\Delta p_t = \alpha\left(p_{1,t-1} - \beta.p_{2,t-1} + c\right) + \Gamma_1\Delta p_{t-1} + \Gamma_2\Delta p_{t-2} + \cdots + \Gamma_{k-1}\Delta p_{t-k+1} + e_t \tag{2.5.5}$$

This is the basic reduced-form framework and we will now turn our attention to the particularities of each price discovery measure. According to Hasbrouck (1995), the term ψe_t is the efficient price innovation whose variance is given by $\psi\Omega\psi'$, where Ω is the residual's e_t covariance. Our first price discovery metric, called *information share* (IS), can be written as:

$$IS_i = \frac{\psi_i^2\Omega_{\mathrm{ii}}}{\psi\Omega\psi'} \tag{2.5.6}$$

IS indicates the proportion of the efficient price variance that is explained by each market and, accordingly, can be used to define who moves first in the price discovery process. However, being a contemporaneous measure, it does not aim to measure the total amount of information impounded on prices. It is also important to emphasize that this interpretation rests on the assumption that the VMA residuals are not correlated. When it fails, Hasbrouck proposes that the system should be calculated under different orderings which have the effect of maximizing the information content of the market in the top of the hierarchy. In the particular case of two assets, one can establish upper and lower bounds or simply define a unique indicator by taking the average IS values as follows:

$$IS_i = \frac{\frac{([\psi F_1]_i)^2}{(\psi\Omega\psi')} + \frac{([\psi F_2]_i)^2}{(\psi\Omega\psi')}}{2} \tag{2.5.7}$$

Where F_j is the Choleski decomposition of the residual covariance matrix for each ordering j so that $e_t = F_j z_t$, where z_t is a zero mean and unit variance vector.

The main drawback of this approach is that the residuals are not orthogonal making it difficult to interpret the results. Choleski bounds can be far from tight, as noted by Grammig & Peter (2010), especially when residuals are highly correlated. With that in mind, Fernandes & Scherrer (2013) proposed a modified IS measure based on a spectral decomposition of the coavariance matrix, Ω, which outperforms both Hasbrouck IS and Lien & Shrestha (2009) modified IS metric[44]. In the eigenvector's space, residuals are orthogonal turning it into a unique measure defined in equation (2.5.8):

$$IS_i = \frac{([\psi S]_i)^2}{(\psi \Omega \psi')} \tag{2.5.8}$$

Where $S = V\Lambda^{1/2}V'$, with V the matrix composed of the eigenvectors in columns and Λ a diagonal matrix of eigenvalues.

Gonzalo & Granger (1995) proposed a decomposition of a cointegrated series into permanent and transitory components that is the basis for a price discovery measure called Component Share (CS). The permanent component must have two properties: 1) it is a linear combination of contemporaneous prices and 2) it is not Granger-caused in the long run by any the transitory component. These assumptions can be used to identify the weights as a function of the speed of adjustment coefficients from the VECM model. Later on, Baillie et al (2002) and De Jong (2002) were able to associate the weights with the long run impact matrix Ψ(1). If we consider an asset trading at two markets (i,j), the CS measure is defined as:

$$CS_i = \frac{\alpha_{\perp,i}}{\alpha_{\perp,i}+\alpha_{\perp,j}} \text{ , or equivalently, } CS_i = \frac{\psi_i}{\psi_j+\psi_j} \tag{2.5.9}$$

Where (ψ_i,ψ_j) refers to the each market´s long run impact matrix derived from matrix Ψ(1) and the vector $(\alpha_{\perp,i}, \alpha_{\perp,j})$ is orthogonal to the speed of adjustment vector α.

For a given market, a low value of the coefficient of adjustment indicates that its contemporaneous price change has a low response to the lagged disequilibrium error: $\beta(p_{i,(t-1)} - p_{j,(t-1)})$. Since the quantity $\frac{\alpha_{\perp,i}}{\alpha_{\perp,i}+\alpha_{\perp,j}}$ is also the weight of market price i on the efficient price, it turns out that the lower the adjustment speed, the higher the weight of a given market to the formation of the efficient price. Note that the difference between IS and CS measures lies in the differential use of the long-run impact matrix which is applied to residuals in the former as opposed to prices in the latter. In fact, simulation-based results from Hasbrouck (2002), Lehmann (2002) and Baillie et al (2002) show that they are compatible in a number of situations. However, weights on the efficient price are equal to the long-run multipliers only up to a scale. So, CS fails to provide accurate efficient price estimates which should be based on the Stock-Watson common trend representation. Besides, Gonzalo-Granger decomposition imposes that the permanent component to be I(1), not necessarily a random-walk what is behind Hasbrouck (2002) critique to the economic interest in such a measure.

Note that both IS and CS measures are originated from a reduced-form representation. Hence, as Lehmann (2002) pointed out, the shocks e_t can be a mixture of information and non-information related frictions. Instead of a reduced form representation, Yan & Zivot (2010) recovered a Structural Moving Average (SMA) model from VECM (2.5.5) that can also provide a measure of relative efficiency. Their model consists of one permanent and one transitory shock. First, the authors assume that the first difference of the price vector has a SMA representation in which the structural shocks $\eta_t = (\eta_t^p, \eta_t^t)$ are serially and mutually uncorrelated.

$$\Delta p_t = D(L)\eta_t \tag{2.5.10}$$

Where the indexes (p,t) stand for the permanent and transitory shocks. The impact of the structural shocks on each market is given by the lag polynomials $d_i(L)$ as follows:

[44] Lien and Shrestha (2009) based their spectral decomposition on the correlation matrix.

$$\begin{pmatrix}\Delta p_{1,t}\\ \Delta p_{2,t}\end{pmatrix} = (D_p(L) \quad D_t(L))\begin{pmatrix}\eta_t^p\\ \eta_t^t\end{pmatrix} = \begin{pmatrix}d_1^p(L) & d_1^t(L)\\ d_2^p(L) & d_2^t(L)\end{pmatrix}\begin{pmatrix}\eta_t^p\\ \eta_t^t\end{pmatrix} \tag{2.5.11}$$

The permanent innovation will be the one that carries new information and, by construction, will impose a one-to-one long-run impact on market prices. The opposite is true for the transitory innovation which arises in the hands of uninformed and liquidity traders and carries no information. Then, the long-run characteristics of the shocks assume the following representation:

$$\lim_{k\to\infty}\frac{\partial E_t[p_{t+k}]}{\partial \eta_t^p} = \lim_{k\to\infty}\sum_{l=0}^{k}\frac{\partial E_t[\Delta p_{t+l}]}{\partial \eta_t^p} = \lim_{k\to\infty}\sum_{l=0}^{k} D_l^p = D^p(1) = 1$$

$$\lim_{k\to\infty}\frac{\partial E_t[p_{t+k}]}{\partial \eta_t^t} = \lim_{k\to\infty}\sum_{l=0}^{k}\frac{\partial E_t[\Delta p_{t+l}]}{\partial \eta_t^t} = \lim_{k\to\infty}\sum_{l=0}^{k} D_l^t = D^t(1) = 0 \quad (2.5.12)$$

Using the BN decomposition, price levels can be written in terms of its long-run impact matrix:

$$p_t = p_0 + \begin{pmatrix}1 & 0\\ 1 & 0\end{pmatrix}\sum_{i=1}^{t}\eta_t + s_t \tag{2.5.13}$$

Although (2.5.13) has the same interpretation as (2.5.4), note that zero mean residuals s_t are defined in terms of structural residuals. To identify the system, SMA parameters must be uniquely defined by the VMA representation (2.5.3). For that purpose, we will see that the long-run impacts (2.5.13) are enough. Applying Johansen (1991) factorization, the long-run impact matrix Ψ(1) can be represented as a function of the VMA coefficients:

$$\Psi(1) = \beta_\perp(\alpha_\perp{}'\,\Gamma(1)\beta_\perp)^{-1}\alpha_\perp' = \xi\alpha_\perp' \tag{2.5.14}$$

To check for the interpretation of the parameter ξ, we refer to Gonzalo & Ng (2001), where the authors separate permanent and transitory components $(\epsilon_t^p, \epsilon_t^t)$ as a function of the reduced-form residuals:

$$\begin{pmatrix}\epsilon_t^p\\ \epsilon_t^t\end{pmatrix} = \begin{pmatrix}\alpha_\perp' e_t\\ \beta' e_t\end{pmatrix} = Ge_t \tag{2.5.15}$$

Applying the VECM residuals e_t to each side of equation (2.5.14), we see that ξ is the long-run response of the market prices to a unit permanent shock. From (2.5.13), we want vector ξ to be equal to one for both prices. This is true only if we make $\alpha_\perp' = \psi$ and ξ a 2x1 vector of ones.

Since permanent and transitory innovations $(\epsilon_t^p, \epsilon_t^t)$ can be correlated, a Choleski triangular factorization allows us to write it as function of the orthogonalized structural shocks:

$$var(\epsilon_t) = HCH' \tag{2.5.16}$$

Where the matrix H is a 2x2 lower triangular matrix with ones in the diagonal elements and C is a diagonal matrix with positive elements. Then, using (2.5.15), structural innovations are defined as:

$$\eta_t = H^{-1}\epsilon_t = H^{-1}Ge_t \tag{2.5.17}$$

The structural representation is exactly identified and its parameters can be recovered from VMA parameters after applying some transformations:

$$\Delta p_t = \Psi(\mathrm{L})e_t = \Psi(\mathrm{L})G^{-1}HH^{-1}Ge_t = D(L)\eta_t = D_p(L)\eta_t^p + D_t(L)\eta_t^t \qquad (2.5.18)$$

Where $D_0 = G^{-1}H$, $D(L) = \Psi(\mathrm{L})D_0$ and $(D_p(L), D_t(L))$ are the columns of $D(L)$ corresponding to (η_t^p, η_t^t), respectively.

This model is primarily aimed at analyzing structural impulse response functions as opposed to the static nature of IS and CS methods, that accounts only for the contemporaneous response to the arrival of new information. However, it is convenient to compute a measure of deviation of each market on its path to the equilibrium price. This deviation can be calculated for each time k by accumulating impulse responses taken from $D_p(L)$ in (2.5.18) as follows: $f_{i,k} = \sum_{i=0}^{k} d_{i,k}^p$. Consider a function that summarizes such deviations when a unit shock in the common price is applied to system (2.5.11).

$$PDEL_i(K^*) = \sum_{k=0}^{K^*} L\left(f_{i,k} - 1\right) \qquad (2.5.19)$$

Where f is the structural impulse response coefficient, i is the index for each market and K^* is some truncated lag period such as f is close to zero.

The function L is arbitrary and the quadratic one will be use throughout. Its interpretation is straightforward, indicating the relative efficiency in terms of price formation. Markets with a high PDEL are slower to recover to equilibrium after a shock in the fundamental price. Based on the same structural representation, Yan & Zivot (2010) provides examples where IS and CS can be misleading pictures of the price discovery efficiency. They propose a measure to correct for cross-market transitory effects that rests on the assumption that covariance residuals are uncorrelated, but the fact that our covariance residuals are highly correlated constrains its application to our analysis. Putnins (2013), by means of simulated data, also concludes that IS and CS provide accurate measures of price discovery only when price series exhibits similar noise patterns.

There is a lot of confusion and lack of precision in the literature concerning what do one means by price discovery. By stating that it refers to the “efficient and timely incorporation of the information implicit in investor trading into market prices”, Lehmann (2002) gives an indication on the two dimensions that we must take into account in order to get an economic perspective. According to Putnins (2013), the term “efficient” refers to the market´s ability to reach the fundamental price, implying a relative absence of noise, to which we can link PDEL metric due to its dynamic nature while computing the accumulated deviation from a permanent shock. “Timely” refers to the relative speed at which new information is incorporated into prices, being closely related to Hasbrouck´s IS metric as far as it measures the contemporaneous contribution of each market to the permanent component innovation, or “who moves first”. Similar concept applies to CS just by taking permanent price instead of innovation.

2.6.Results

2.6.1.VECM

We will start our analysis with the VECM results (equation 2.5.5) for the whole sample period. From now on, we will refer to the vector of prices as $p_t=(s_t , f_t)$, where s_t is the spot market price and f_t, is the futures price corrected as in (2.4.1). It is usually recommended to work with higher than usual lag lengths in intraday analysis to account for the high frequency dependencies between prices. Although standard criteria provided divergent recommended values, it is clear from Table 18 that coefficients are stable irrespective of the lag length we employ. So, our reference case will consider a lag length equal to 10 and we will check results’ robustness in Section 2.6.3.

The speed of adjustment toward equilibrium is determined by the magnitude of α and, restricting the cointegration coefficient to (1,-1), it measures the adjustment to deviations from CIP[45]. We reject the null hypothesis (α=0) for the spot market adjustment coefficient, meaning that it reacts to such deviations. The negative sign means that when facing a negative disequilibrium error, that is, when futures increases above the arbitrage conditions imposed by CIP, spot reacts accordingly by raising its price. The low adjustment value suggest that this correction is slow given that only 3.2% of the disequilibrium is adjusted in one time-period (five minutes). In contrast, we conclude that the futures market does not respond to equilibrium deviations by the fact that the adjustment speed is not significant. It is important to note that, similar to Garcia & Ventura (2012), the speed of adjustment is lower in the futures market what, according to Hasbrouck (2006), indicates a more dominant market. Finally, LR cointegration test for binding restrictions, which tests the null of no cointegration against the known alternative of rank one, supports the existence of a (1,-1) cointegration vector in all cases.

Table 18: Coefficients for the VECM regression from January/2008 to June/2013 ($\Delta p_t = \alpha(s_{t-1} - f_{t-1} + c) + \Gamma_1 \Delta p_{t-1} + \Gamma_2 \Delta p_{t-2} + \cdots + \Gamma_{k-1} \Delta p_{t-k+1} + e_t$)

	Lag Length = 5		Lag Length = 10		Lag Length = 30	
	Spot	Futures	Spot	Futures	Spot	Futures
α	-0.044 (10.6)	0.001 (0.3)	-0.032 (7.5)	0.001 (0.1)	-0.022 (5.1)	0.001 (0.2)
β	1	-1	1	-1		-1
c	0.0003		0.0003		0.0003	
Residual correlation	0.95		0.95		0.95	
R^2	0.03	0.01	0.03	0.01	0.03	0.01
Number of observations	140,089		140,084		140,074	

Note: Lag coefficients are omitted
In parenthesis, are the t-statistics.

2.6.2.Price Discovery in the whole sample

We will explore the different price discovery metrics described in Section 2.4. We will begin with our reference case that employs a VECM with lag length of 23 and five-minute intraday price frequency. Remember that the IS metric reports the contribution of each market to the variance of the common price and is calculated departing from a reduced-form representation. The VMA system could be identified by applying the Choleski decomposition on the covariance matrix, as proposed by Hasbrouck (1995), what would allow us to calculate lower and upper bounds depending on the variable ordering. However, under this identification procedure, they are not helpful to identify as bounds are not tight enough. Although such wider intervals are well documented in the literature (see Hasbrouck (2003), Grammig & Peter (2010)), what makes it remarkable is the high level of correlations (0.90) among residuals. Hasbrouck´s proposition to increase sampling frequency to avoid residual correlation is not possible in our study due to the reasons outlined in Section 2.4. So, for the remainder of the paper, IS values will refer to spectral decomposition as described in Section 2.5.

The results in Table 19 show that futures market dominates the exchange rate price discovery in all perspectives and taking confidence interval into account. It responds for 66.2% of the variation in the permanent shock and for 97.4% of the efficient price composition. But why CS values are considerably higher than IS ones? We can attribute to the fact that CS is not dependent on residual correlation, suggesting that the decomposition procedure yields an underestimated IS value. Also, the higher value of PDEL indicates a greater efficiency loss in the spot market and thus a lower contribution to the price discovery process. Our results are in agreement with the order flow findings of Garcia & Ventura (2012). In fact, Rosenberg & Traub

[45] Taking risk country into account by applying “cupom cambial”.

(2009) already accounted for the compatibility between the order flow approach and price discovery.

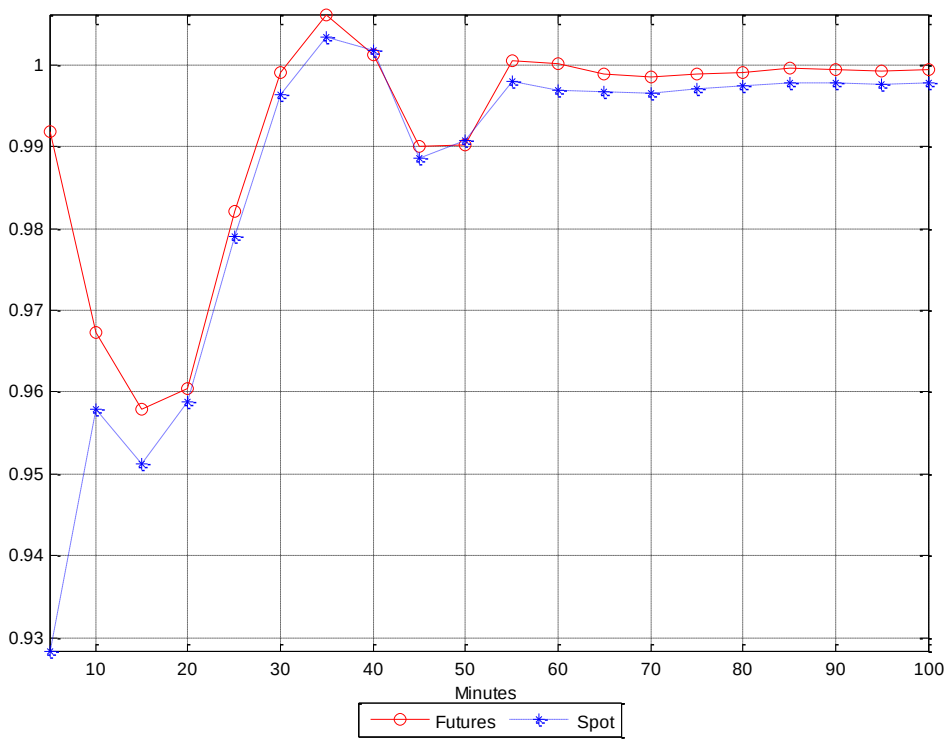
Table 19: Price discovery metrics between January 2008 to June 2013

Measure	Spot	Futures
IS	33.8% [33.0%;34.7%]	66.2% [65.3%;67.0%]
CS	2.6%	97.4%
PDEL	0.0120 [0.0095;0.0137]	0.0050 [0.0047;0.0055]

Note: Lag length=10.
Frequency= 5 minutes.
5% confidence interval in brackets.

Moving to the structural representation, dynamic behavior can be analyzed through the impulse response functions in Graph 7, which shows each market's response to a unity fundamental price innovation. The immediate effect, up to 30 minutes after the shock, both markets underreact but futures one is closer to the fundamental price in the first 15 minutes and, from that point, prices move together. Although the PDEL indicator suggests that the futures market is more efficient, the convergence of both markets is obtained almost simultaneously, approximately 55 minutes after the fundamental price innovation.

Graph 7: Impulse response functions from January 2008 to June 2013



Note: Lag length=10
Frequency= 5 minutes.

Even prior to the evidence presented in Table 19, our intuition based on the relative market size would direct us to point out the futures market as the dominant one. But market share is far from being the factor that uniquely defines the dominant market. Based on daily data, Rosenberg & Traub (2009) analyzed price discovery in the US spot and futures currency

markets in two sample periods: 1996 and 2006. In 1996, futures market dominance has been confirmed by both IS and CS metrics within a range of 80%-90% depending on the foreign currency. In 2006, there is a complete reversal given that the spot one played the dominant role. In both periods, spot market had, by far, higher volume shares. An issue that immediately arises is to find what factors could drive price discovery to the lower share trading venue and, more important, discuss the reasons why it did not apply to the Brazilian FX market.

The first potential factor is the incidence of informed trading. In theory, there are no *a priori* restrictions for it to be taken in the satellite market. According to Rosenberg & Traub (2009), the literature lists two main reasons why informed traders could prefer a satellite market: greater anonymity or higher speed of transaction execution. Back to the Brazilian market, anonymity should be greater in the futures market since noisy trading in high liquid markets should help to obscure informed trading. In a German stock market study, Grammig et al (2001) found that the probability of informed trading is significantly lower in environments with lower degrees of anonymity. Spot market highly decentralized environment does not favor the transaction execution motivation either. But even if we totally agree that informed trading takes place predominantly at the futures market, it is far from consensual to what degree larger shares of informed trading are proportional to price discovery figures. This controversy can be illustrated by the study of Easley et al (1998) for the 50 most liquid US stocks. The authors showed that trading in the options' market, the satellite market, contained price relevant information what leads us to conclude that a non-zero share of informed trading suffices to influence prices.

Transparency is a second factor that could be determinant in the price discovery process. In 1996, although US spot FX market had higher volume share, it lacked transparency. In 2006, higher transparency levels allowed the positive association between liquidity and price discovery to emerge, as reported by Rosenberg & Traub (2009). In Brazil, while futures transactions are all electronically made and instantaneously subjected to the clearinghouse, spot ones are not shared by all investors and traded in multiple decentralized platforms.

Recent papers on the relationship between HFT and price discovery can offer an additional explanation to this result. According to this point of view, HFT can anticipate subsequent price movements, enhancing price discovery and efficiency. This is the conclusion of the work of Brogaard et al (2013), which find that they trade in the direction of permanent prices and in the opposite direction of transitory ones. Hasbrouck & Saar (2013) also find empirical evidence that market quality can benefit from HFT by reducing spreads and volatility and increasing market depth. Kirilenko et al (2011) points out, however, that this benefit can be controversial under extreme circumstances. The authors analyzed the stock market in 6th May of 2010, when in a short period stock market experienced a sudden drop in prices of more than five percent, an event denominated Flash Crash. They concluded that HFT didn't trigger it, but they contributed to it.

Although most part of the literature is based on stock market databases, estimates point to the presence of HFT[46] in the FX market. It is also realistic to infer that high frequency traders are likely to be more actively trading in the futures market, where all transactions are electronically-based and surely the most organized and less restricted one. It is where it could better protect anonymity and enhance the use of private information. Taking the benefits of HFT into account together with its higher transparency levels, it comes as no surprise to conclude that the futures market is dominant both in terms of speed and efficiency.

2.6.3.Changing the Lag strucuture

Using a sampling frequency of five minutes and the whole sample, we will assess to what extent changing the lag structure interferes in the results. From Table 20, we can rule out any

[46] Based on BVMF information, Nakashima (2012) estimates in 16% the contribution of HFT to the total traded volume in the FX futures market

misspecification due to the lag length choice. In general, we reinforce the interpretation that futures market dominates the price discovery process with IS point estimates in a tight range [62.9%, 67.3%] as much as CS ones [86.2%, 98.4%]. Moreover, confidence intervals are distant enough to attest for the statistical significance and conclude for the difference in IS and PDEL values. PDEL metric also indicates a futures superior efficiency, except when lag length is equal to 1, when we cannot reject the equality between spot and futures market.

Table 20: Price discovery metrics between January 2008 to June 2013 for different lag lengths

Lag Length	IS		CS		PDEL	
	Spot	Futures	Spot	Futures	Spot	Futures
1	37.1% [36.3%;38.0%]	62.9% [62.0%;63.7%]	13.8%	86.2%	0.00045 [0.00029;0.00067]	0.00042 [0.00037;0.00049]
5	33.6% [32.8%;34.3%]	66.4% [65.7%;67.2%]	1.6%	98.4%	0.0185 [0.0126;0.0243]	0.0060 [0.0053;0.00070]
30	32.7% [31.8%;33.4%]	67.3% [66.6%;68.2%]	6.4%	93.6%	0.0710 [0.0695;0.0722]	0.0650 [0.0635;0.0683]

Note: Frequency= 5 minutes.
5% Confidence interval in brackets.

2.6.4.Changing the frequency of the data

What should be the impact of frequency choice in the analysis? First of all, sampling prices at lower frequencies should alleviate problems associated with the lower liquidity of the spot market such as non-trading and market microstructure. Second, we assumed that any significant difference between OTC and BVMF prices is not sustainable for a long period of time. Apart from the cost of information loss, working with lower frequencies make it possible to the slower market to adjust, suppressing any information advantage from the dominant market.

In this sense, it is clear from Table 21 that lower frequencies tend to favor spot market both in term of efficiency (PDEL) and contemporaneous variance contribution (IS). Note also that efficiency losses are almost negligible in daily frequency indicating that adjustment towards equilibrium takes less time. Spot market CS values are negative for all sampling frequencies implying that spot and permanent prices moved in opposite directions. Yet, according to Korenok et al (2011), price discovery metrics can lead to erroneous interpretation when CS weights are negative. The results, thus, confirm the adequacy of the five-minute one as our leading scenario.

Table 21: Price discovery measures between January 2008 to June 2013 (10 lags)

	10 minutes		30 minutes		Daily	
Measure	Spot	Futures	Spot	Futures	Spot	Futures
IS	29.6% [28.2%;30.9%]	70.4% 69.1%;71.8%]	34.9% [33.0%;36.9%]	65.1% [63.1%;67.0%]	41.9% [40.2%;43.1%]	58.1% [56.9%;59.3%]
CS	-33.3%	133.3%	-41.6%	141.6%	103.5%	203.5%
PDEL	0.032 [0.028;0.043]	0.032 [0.030;0.037]	0.013 [0.012;0.017]	0.014 [0.011;0.016]	0.0014 [0.0014;0.0019]	0.0018 [0.0016;0.0019]

Note: Lag length= 20 (Frequency= 10 minutes.) and Lag length=5 (Frequency= 30 minutes.) and Lag length=1 (Frequency= 1 day)
5% Confidence interval in brackets.

2.7.Price discovery in sub-samples

Although previous results point to futures market dominance, it will be particularly interesting to investigate its dynamics over sub-samples. To begin with, it is fair to conjecture that price discovery process might be influenced by market volatility. Uncertainty potentially triggers investors' search for an equilibrium price and action of informed traders eventually drive prices to equilibrium. Our assumption is that, in higher volatility periods, markets are subjected to more fundamental shocks and, thus, price discovery process is more active and the most informative market will play a leading role. As you can see in Graph 9 in Annex B, from the 3th quarter of 2008 to the beginning of 2009, realized volatility[47] figures take extreme values. In the remaining sample, despite periods of low and stable volatility levels dominate, we can see recurrent short periods of volatility bursts.

Taking this into account, we split the database in two sub-samples according to the realized volatility. Since each sub-sample series is restricted by convergence[48] issues, a low (high) volatility regime has been constructed with five-minute prices from the 160 least (most) volatile days. Price discovery metrics, presented in Table 22, show that futures market dominance is more evident in the high volatility regime what, according to our assumption, means that it is the most informative one.

Table 22: Price discovery metrics between January 2008 to June 2013

	Low volatility		High volatility	
Measure	Spot	Futures	Spot	Futures
IS	47.4% [45.4%;49.4%]	52.6% [50.6%;54.6%]	37.6% [35.4%;39.8%]	62.4% [60.2%; 64.6%]
CS	31.7%	69.3%	0.2%	98.8%
PDEL	0.000100 [0.000045;0.000170]	0.000039 [0.000017;0.000059]	0.000260 [0.000071;0.000510]	0.000070 [0.000049;0.000094]

Note: Lag length according to Schwarz criteria. Frequency= 5 minutes. 5% confidence interval in brackets.

In Table 23, where price discovery metrics are calculated by semester[49]. Since futures metrics are above 50% in all periods, results support the general conclusion that the futures market moves first in the price discovery process. Despite level differences between IS and CS metrics, both are rather compatible if we take into account the joint upward and downward shifts. It is important to note, though, that price discovery dynamics is more volatile than the market share evolution would imply. While we observed a progressively larger proportion of futures market share, there are periods where spot market contribution was very close to 50%, probably due to institutional and market factors that will be further discussed.

[47] Realized volatility has been calculated as the sum of the five-minute squared returns with no correction for microstructure.

[48]We identified a convergence problem associated with price discovery methodology. When the eigenvalues' sum of the VECM parameters' matrix is above unity, both markets do not converge when facing a permanent shock. We are grateful to Cristina Scherrer and Marcelo Fernandes for this contribution.

[49] At first, we tried to split the sample on a monthly basis in order to match with financial reports that are released in identical frequency. We only obtained reliable price discovery metrics in sub-samples with at least six-month data, see note 48 for details.

Table 23: Price Discovery metrics by semester

Semester	IS		CS	
	Spot	Futures	Spot	Futures
I.2008	29.7% [28.6%;30.9%]	70.3% [69.1%;71.4%]	10.9%	89.1%
II.2008	33.7% [32.5%;35.0%]	66.3% [65.0%;67.5%]	16.8%	83.2%
I.2009	36.7% [35.6%;37.8%]	63.3% [62.2%;64.4%]	20.1%	79.9%
II.2009	23.0% [22.0%;24.0%]	77.0% [76.0%;78.0%]	22.8%	77.2%
I.2010	45.7% [44.4%;47.1%]	54.3% [52.9%;55.6%]	35.9%	64.1%
II.2010	39.0% [37.9%;40.1%]	61.0% [59.9%;62.1%]	36.3%	63.7%
I.2011	11.8% [10.9%;12.7%]	88.2% [87.3%;89.1%]	21.9%	78.1%
II.2011	44.6% [43.4%;45.9%]	55.4% [54.1%;56.6%]	48.5%	51.5%
I.2012	40.0% [38.9%;41.1%]	60.0% [58.9%;61.1%]	25.9%	74.1%
II.2012	37.4% [36.5%;38,2%]	62.6% [61.8%;63.5%]	37.8%	62.2%
I.2013	33.3% [32.5%;34.1%]	66.7% [65.9%;67.5%]	24.6%	75.4%

Note: Lag length was calculated for each sub-sample according to Schwarz criteria
5% Confidence interval in brackets.

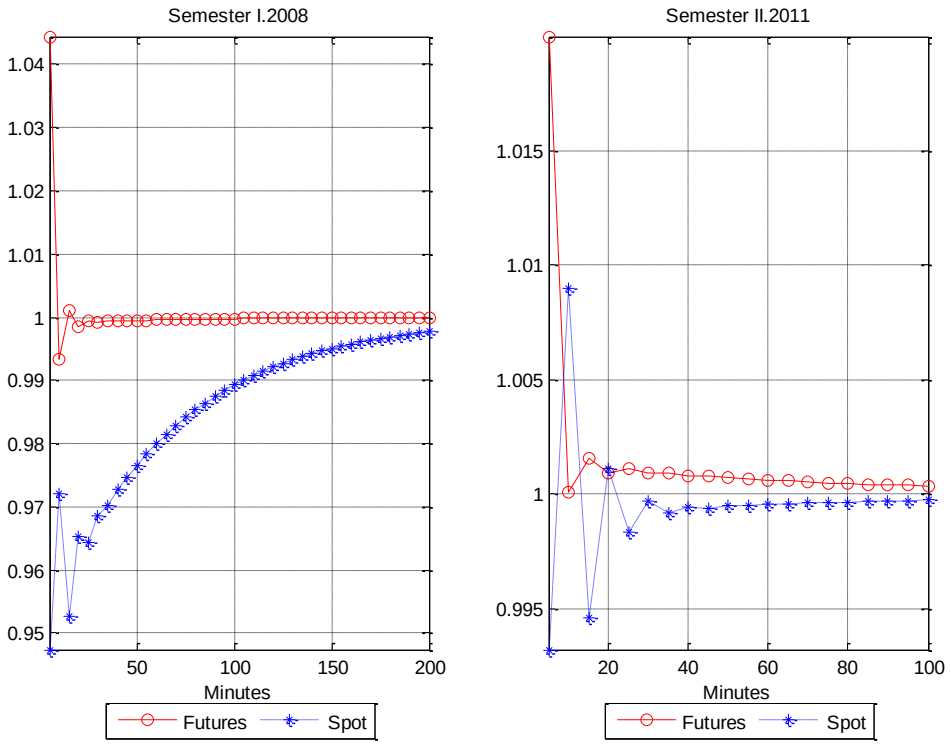
In Boyrie, Pavlova & Parhiagan (2012), the authors found an IS value of 77% for the Brazilian futures market[50]. When they break in sub-samples, they found that spot market IS was above 55% between October 2007 and October 2008, i.e., around the financial crisis epicenter. Since this finding is at odds with Table 23, it is important to state its differences. First, Boyrie, Pavlova & Parhiagan (2012) used a daily sampling frequency, raising the “data thinning” issue reported by Hasbrouck (2002). In addition, we are not able to attest for its validity[51] provided that the authors did not report CS weights.

[50] Their sample period ranged from January 2005 to March 2011.

[51]Remember, from Section 2.5.4, that CS weights were negative when we used daily data, making price discovery values difficult to interpret.

Concerning the efficiency dimension, we shall analyze impulse response functions (IRF) under extreme scenarios. In Graph 8, we report the IRF for the first semester of 2008 where we obtained the highest CS futures value and also the one for second semester of 2011, the lowest one. In the first, we can see that the behavior of each market presents a clearer superior pattern when compared to Graph 7. Now, futures market reaction is not only superior, but convergence to the equilibrium is quickly obtained, 15 minutes after the permanent shock while the spot market takes more than two hours to converge. In the latter, where price discovery is almost evenly divided, a puzzling relative response is generated and no clear sign of dominance can be identified.

Graph 8: Impulse response function for selected semesters



Note: Lag length was calculated for each sub-sample according to Schwarz criteria

As we have seen, results are not uniform across the sub-samples. Stated differently, there is sufficient indication to infer that price discovery is not a stable process. But what factors could determine the relative contribution to price discovery? From a practical point of view, there are situations where demand imbalances in one market could interfere in price discovery metrics. Take the example of spot demand as inferred by Brazilian current account (CC) figures. Since 2008, there is a brutal rise in CC deficit which, up to this moment, has been covered by primary market inflow. However, how BCB is dealing with transitory spot demand? Since it has the acknowledged goal of preserving international reserves, it usually resorts to swap[52] interventions. When it intervenes through the derivatives market, BCB offers hedge for banks which, in principle, allows them to meet the private agents' demand. By doing this, it postpones spot demand and expect for a better financial scenario to recover this imbalance. In this line of thinking, a proper way to measure such spot market pressure is to compare BCB interventions with the inflow from the primary market.

[52] Swap is a forward contract where BCB assumes a short position in FX futures and a long position in domestic interest rates.

Understating the role of each participant is also vital to infer price pressures originated in the futures market. First, FX bank positions are altered by the demand for foreign currency in the primary market. Due to regulation restrictions, the exposure to FX risk is offset in the derivatives market. Hence, we will usually see banks holding opposite positions in the futures and spot markets of similar magnitude. Non-financial investors assess market to hedge for FX risks in the primary market, holding matched positions in long term futures. Institutional investors, whether domestic or external, are the ones we must take a careful look as long as they can take open positions in either directions. Since futures contracts are liquidated in the domestic currency, speculative demand does not incur in spot market demand, but can interfere in its price through arbitrage.

In I.2008, a period of high CS for the futures market, total capital inflow from the FX primary market[53] averaged US$ 14.9 billion exactly matching the average BCB spot intervention amount. In addition, BCB heavily intervened through reverse swaps amounting US$ 13.2 billion on average. Institutional investors were almost neutral, holding an average short position of US$ 600 million. In II.2008, spot and swap interventions were executed in the wake of the lack of liquidity in financial markets. Swap interventions' volume, though, was ten times higher than the spot ones, with IS and CS values indicating clear futures dominance. In both semesters of 2010, where price discovery results were mixed, BCB did not intervene in the futures market through swaps, only in the spot one. In I.2010, futures position from institutional investors were neutral and spot interventions averaged US$ 14.1 billion while total FX inflow were significant lower (US$ 3.4 billion). In II.2010, spot interventions were again superior to capital inflow (US$ 27.5 billion against US$ 21.0 billion) and short positions in the futures market averaged US$ 10.7 billion. Up to this point, we can figure out two possible price discovery factors. The first is the misalignment between capital flow and spot interventions that exerts a potentially demand pressure on the spot market, rising its IS and CS values. The second one refers to the level of futures market interventions (swap or reverse swaps), this one acting in the direction of higher futures IS and CS values.

Adding up more semesters to the analysis, the impact of the above factors is reinforced. In I.2011, spot interventions were again matched with capital inflow and, in a similar pattern to that verified in I.2008. BCB resorted heavily to reverse swap interventions (US$ 14.7 billion, on average), resulting in higher CS and IS futures values. In II.2011, the misalignment between spot interventions and capital flow had been introduced again, but this time it occurred in the opposite direction, i.e., high capital flow (US$ 25.4 billion) as opposed to low spot intervention volume (US$ 11.1 billion). As a result, almost half of the price discovery has been credited to the spot market.

The effect of interventions in the FX market has been extensively studied in the literature. It is well known that non-sterilized ones impact FX rates by the interest rate channel. As far as sterilized interventions are concerned, its effects are less consensual, although recent studies have been able to find significant effect. Using intraday data, Lahura & Vega (2013) report an asymmetric effect on Central Bank intervention on Peru, only when it sells foreign currency. When Central Bank is at the buy side, market participants do not adjust its permanent price expectations because the intervention goal is aimed at increasing reserves, not to influence prices. Echavarría et al (2013) also report a significant price effect of pre-announced interventions and capital controls on the Colombian spot exchange rate. But intervention effect is not limited to first order effects, as Chari (2007) finds. According to the author, central bank interventions lead, on average, to widening spreads and increasing levels of volatility.

Kohlscheen & Andrade (2013) reported the presence of short-term effects of swap interventions on the spot FX market in Brazil. Note that, due to the singular configuration of Brazilian FX market, this result should be put in perspective as a general policy recommendation. Since futures market is responsible for the most part of price discovery in Brazil, fundamental price will incorporate a high share of the intervention shock and spot one will adjust accordingly. In addition, by directly interfering in futures market equilibrium, BCB

[53] BCB releases the FX flow from the primary market on a monthly basis.

signals its private information through that market, increasing IS and CS futures shares endogenously. We showed, though, that there are moments where Brazilian spot market share in the fundamental price is close to 50% and, in most countries, the opposite occurs, i.e., spot market responds for most part of the variation in fundamental price. In such instances, it may be the case that a futures intervention will be interpreted as noise rather a signal to market participants.

It is also worth to provide an analysis of FX public policies over the sample period. Until August 2008, FX policy was directed towards avoiding excessive capital flows and, consequently, the domestic currency appreciation trend. In that period, we experienced tax[54] increases and changes in the rule that regulated the dollar amount exporters could hold abroad. Around September/October 2008, as the financial crisis reached its peak, capital outflow induced a complete reversal in FX policies. Besides massive FX intervention volumes, tax reduction and a swap agreement[55] with FED allowed the market return to normality. In 2009 and 2010, monetary expansion and the prevalence of low interest rates in the central economies induced international portfolio rebalancing towards a greater share of emerging countries assets. Thus, the increasing capital inflow inaugurated a period of tax increases where taxes varied according to the investment holding period, aimed at reducing the speculative capital inflow proportion.

In 2011, FX policy makers concentrated its effort so as to avoid domestic currency appreciation, but there was one regulatory decision that attracts special interest to our study. In July 2011, BCB instituted a reserve requirement of 60% for holding short positions in the futures market in excess of US$ 1 billion. Note that while all previous measures shared the intention of avoiding speculative capital inflows, the tools employed had an indirect and even effect to both FX markets: spot and futures. This is the only measure that directly affects only one of the markets and, more importantly, it impacted a potential price discovery driving force: the position of institutional investors in the futures market. With a six-month sub-sample, it is difficult to measure and directly associate this policy to the lowest futures market price discovery value. But the alleged “coincidence” allows us to suspect that its impact has not been negligible. As capital inflows started to flow back to central economies in mid-2012, this reserve requirement have been progressively alleviated, in conjunction with tax rates and investments’ holding periods.

To sum up, the undisputed futures market dominance over sub-samples comes from the fact that it is the most transparent and liquid one. However, we found that the ups and downs in the relative price discovery figures can be associated with some specific factors that put spot market in a greater position than its market share would indicate. Spot market disequilibrium, measured as the difference between capital inflow and BCB interventions, might play a major role. When there is no spot market disequilibrium and, still, BCB intervenes in the futures market through swaps, it supposedly increases futures market dominance. Policy actions, such as the reserve requirement of July 2011, whose impact is asymmetric, might also be important. Far from being exhaustive, this Section aimed at giving insights on the possible price discovery drivers. Besides, the fact that we are not able to compute smaller sub-samples restricts our analysis to a great extent.

2.8.Conclusion

This paper examines where prices are determined in the Brazilian FX market. In order to perform this investigation, we applied price discovery methodology based on a high-frequency

[54] In Brazil, the Finance Minister regulates tax rates. Changes in the tax associated with financial transactions (IOF- “Imposto de Operações Financeiras”) are the most commonly used tool to increase capital controls.

[55] In order to provide market liquidity in dollars. FED and BCB set up a swap operation up to US$ 30 billion dollars.

database covering the period that starts at January 2008 to June 2013. Through a variety of metrics well established in the literature, we provide robust evidence that futures market dominates the price discovery process. Since prices are linked by arbitrage conditions, the results enable us to conclude that prices are formed in the futures and, then, spot market adjusts to restore equilibrium and eliminate short-run deviations.

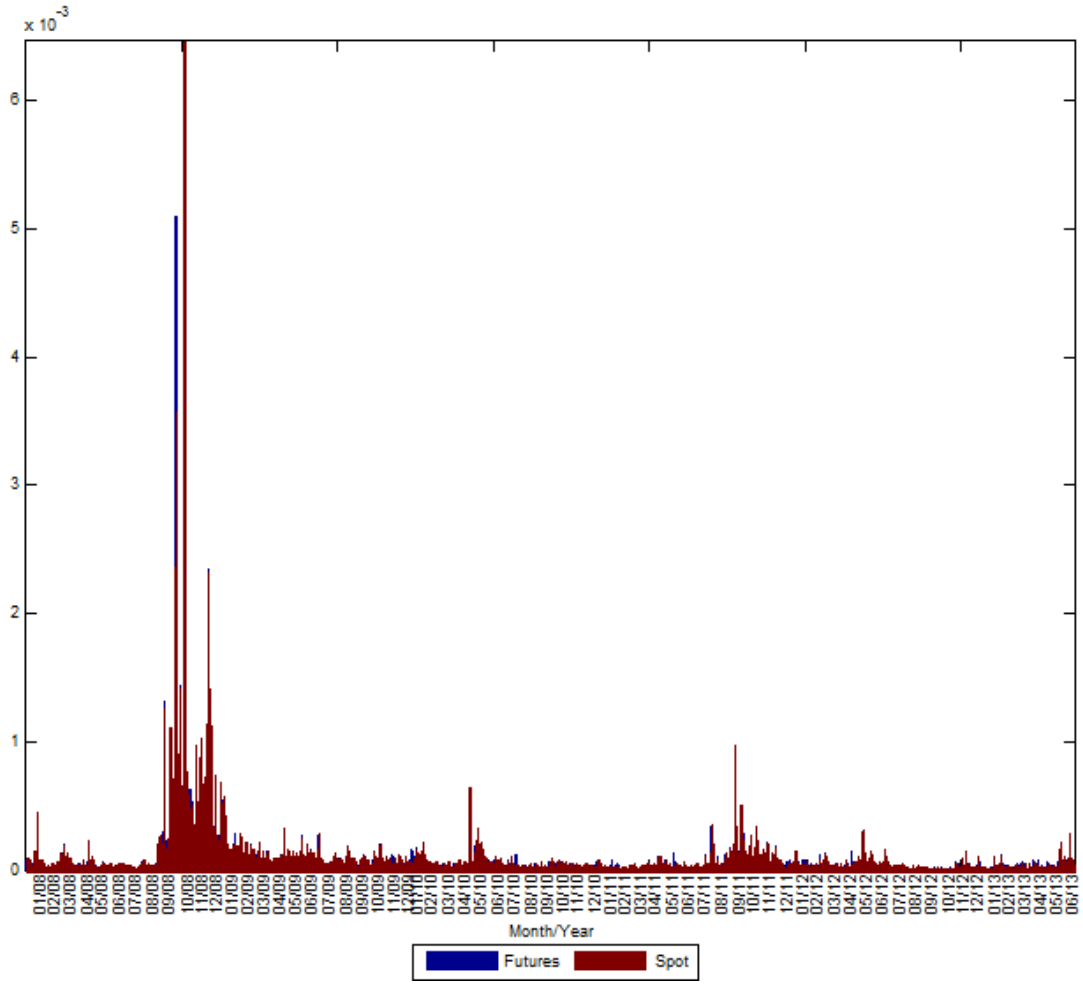
There are some reasons why this result naturally arises from microstructure considerations. Spot market transactions are highly decentralized, distributed among several intermediaries. Besides, government regulation limits its access to a few authorized financial institutions with direct impact on relative liquidity which are nine times higher in the futures market. The futures market, in turn, is characterized by publicly-traded prices and broad access to financial and non-financial institutions. These features result in higher transparency levels and stimulate HFT, both key market efficiency drivers. It has progressively incurred in a change in its planned design in order to satisfy the high demand for FX transaction from economic agents, resulting in a high proportion of short-term futures contracts traded, with a month or less to maturity. Under this background, our findings bring together the empirical methodology with overall market intuition. The IS metric, for instance, point out that 66.2% of the variation in the fundamental price shock is originated in the futures market. When it comes to price composition, the CS value indicates that it responds for 97.4% of the fundamental price. It is also more efficient, that is, it is faster to recover to equilibrium.

We also investigated whether results are robust to sub-samples. First, we show that futures market yet dominates in high volatility regimes, where supposedly markets are subject to more frequent shocks and the price discovery process is supposedly more active. When we break in sub-samples by semester, IS and CS figures show non-trivial variations. We have seen that, during the database period, the Brazilian FX market suffered various degrees of interventions and capital controls and its currency (BRL) experienced periods of appreciation and depreciation. We are able to identify spot market offer and demand disequilibrium, central bank interventions and institutional investors' pressure in the futures market as potential explanatory factors. We can also attribute variation to a huge regulatory measure that restricted futures transactions in the second semester of 2011.

Future research should investigate the relationship between central bank intervention and price discovery. With the current work, we are able to offer general evidence on this subject, but an analysis of high frequency prices surrounding interventions shall give light to the determinants of this relationship, its intensity and uncover its transmission mechanism. Conditional on data availability, increasing the sampling frequency can improve efficiency of price discovery estimates and minimize data thinning. Finally, there is room to improve theoretical models and overcome convergence problems in order to allow price discovery metrics in smaller sub-samples.

2.9.Annex B

Graph 9: Daily realized volatility estimates for the spot and futures markets between January 2008 and June 2013



3Modeling realized volatility: measuring forecasting performance and economics gains

3.1.Introduction

Given the growth of financial markets and the increasing complexity of its securities, volatility models play an essential role to help the task of risk management and investment decisions. Since realization of volatility returns based on daily data is not observable, the traditional approach is to invoke parametric assumptions regarding the evolution of the first and second moments of the returns, which is the idea behind ARCH and stochastic volatility models. Nevertheless, these models fail to capture some stylized facts such as autocorrelation persistence and fat tail of returns. The availability of intraday data opens up the possibility of approximating volatility directly from asset returns. The use of an observable variable, in turn, facilitates the task of dealing with problems that involves a significant number of assets. Indeed, traditional methods suffer from the curse of dimensionality, which is to say, the difficulty of these methods to handle with a wider range of assets.

The advantages of realized measures have been extensively analyzed in the recent period, when technological barriers have been gradually surmounted so as to provide the kind of data necessary to its calculation. Andersen et al (2003) compared it to traditional methods and confirmed its superiority in terms of forecasting performance. Identical conclusion has been reached by many concurrent studies, like Engle et al (2008). Previous findings relating microstructure parameters and volatility were revisited considering realized measures. Chan & Fong (2006), for instance, found that trading volume is the main factor driving the relationship between volume and realized volatility, as opposed to studies that pointed out order imbalance as the most important one. In Brazil, Carvalho et al (2006) found that returns displayed a normal distributional when standardized by realized measures, a useful property concerning risk management purposes, namely Value-at-Risk statistics. The authors based their conclusions on a sample of the five most liquid stocks traded at the domestic stock exchange, sampling at a 15-min frequency. In spite of the apparent consensus over the subject, there are many relevant issues that deserves attention, in particular the bias originated by microstructure noise and measurement errors. McAleer & Medeiros (2008) documented a review of the literature, stressing the future improvements that must be made in order to deal with such biases.

The objective of this paper is to propose a model of realized variance-covariance of a portfolio consisted of the most liquid stock assets of BMF&Bovespa, the Brazilian stock market exchange. In addition, we aim to evaluate the economic gains associated with following a volatility timing strategy that considers this realized measure instead of traditional volatility models.

This paper contributes to the literature in many aspects. First of all, we employ a unique database composed of all the stocks traded at the Brazilian stock market. The fact that Brazil is an emerging market raises the issue whether adaptations to models originally designed to fit consolidated markets are required. Moreover, the forecasting model of realized volatility has been applied to a multivariate framework. Alone, this is not an innovation to the literature. However, we employ a greater than usual number of assets and it is not straightforward to infer that the results will continue to hold.

Our database consists of high frequency transactions prices from the twenty most liquid stocks from the Brazilian Stock Exchange, BMF&Bovespa. It covers the period from February 2006 to January 2011. We measure economic gains considering an investor that takes conditional volatility forecasts as the main parameter in the portfolio optimization problem: the

so-called volatility timing strategy proposed by Fleming et al (2001). Volatility forecasts were obtained by means of a multivariate version of Corsi's Heterogeneous Auto-Regressive (HAR) model.

We find that economic gains associated with realized volatility increase proportionally to the target return. We also show that, when target returns are close to the risk-free, portfolios weights are heavily dependent on the risk-free asset. This finding allows us concluding that realized volatility performs better for increasing levels of risk. Using the unconditional mean as a reference for expected returns, an investor would be willing to pay substantial positive fees to switch from a portfolio based on forecasts taken from traditional volatility methods to one based on realized volatility forecasts, when target returns are superior to 15% a.y.. When expected returns are bootstrapped, although fees are still positive on average, high standard deviation values lead us to conclude that utility gains are equal at a statistical viewpoint. Actually, when estimation risk is significant, average portfolio returns are far apart from target returns irrespective of the volatility measure used, which is an indication that economic gains of realized volatility are offset by estimation risk.

We also perform robustness checks that confirm that, when estimation risk is negligible, economic gains are robust to changes in the parameters of the economic utility and of the optimization problem. Finally, we conclude that the inclusion of an external risk factor, aimed at adapting the model to an emerging economy, do not add in terms of utility gain.

Our results represent an important input to the applicability of realized volatility as a reference for risk estimates for Brazilian stocks. It provides additional evidence to the literature that links positive economic values associated to realized volatility, as Christoffersen et al (2012), in their study of the benefits of realized volatility measures for option pricing, and Fleming et al (2003), which used it as an input for a volatility timing strategy based on four assets traded at the US futures market.

The text is organized as follows. In Section 3.2, we provide key realized volatility concepts. Next, we will explain database sources and how we computed multivariate volatility. In Section 3.4, we present our version of HAR model and describe its application to a multivariate setting. Then, we present the methodology behind economic gain evaluation forecasting and discuss results and robustness checks in Section 3.6. Finally, we offer our concluding remarks in Section 3.7.

3.2.Theoretical background: Realized Volatility

We will provide a brief review of the theoretical framework underlying the realized volatility (RV) measure. The theory of Quadratic variation is the baseline to understand how we obtain this direct measure of volatility.

We begin by assuming that logarithm prices (p_t) follow a continuous-time diffusion process given by:

$p_t = p_0 + \int_0^t \mu(s).ds + \int_0^t \sigma(s)dW(s)$, where W(t) is a standard Brownian motion, μ(t) is the mean process with finite variation and σ(t) is the instantaneous volatility which, by definition, is a positive process.

Over the time interval [t-k,t], the continuous compound return ($r_{t,k} = p_t - p_{t-k}$) is given by the following process:

$$r_t = \int_{t-k}^t \mu(s).ds + \int_{t-k}^t \sigma(s)dW(s) \tag{3.2.1}$$

When we sum up the contribution of the mean component, μ(t), to the variation of returns we will find out it can be ignored. This is because $\mu(t).dt$ is of lower order of magnitude when

compared to the second term $\sigma(t)dW(t)$ in terms of second order properties (see Andersen & Benzoni (2008)). Then, Quadratic Variation (QV) is defined as follows:

$$QV(t,k) = \int_{t-k}^{t} \sigma(s)^2 ds \qquad (3.2.2)$$

Suppose that one has all available information on intraday returns of an asset making it possible to calculate Realized Volatility (RV):

$$RV_t = \sum_{i=1}^{T} r_t^2 \qquad (3.2.3)$$

With no microstructure noise, Andersen et al (2003) showed that QV converges in probability to RV. So, RV, defined as the sum of squared intraday returns, is the discrete version of the quadratic variation process. This is done by sampling returns in a predetermined frequency. However, it does not come without a cost as it raises a set of issues related to microstructure of transaction that will be discussed in Section 3.3, as we describe the construction of the database.

3.3.Database construction

We use a unique database that contains all transactions (deals, bids and asks) of stocks traded at BM&FBovespa, the Brazilian company responsible for intermediating equity market transactions. The time series ranges from February/2006 to January/2011 and we select the twenty stocks listed in Table 24. There are two main reasons behind the outcome of this selection. First of all, we want to work at the highest possible frequency and minimize microstructure biases that arise when working with stocks with low liquidity. As we will see, all of the selected stocks meet this liquidity criterion. Besides, since we are doing out-of-sample forecasts that require a large number of days to work properly, we rule out stocks that belong to the database for less than 300 trading days.

Stocks in Brazil are divided into preferred (PN) and common (ON) shares. The main difference is that the first type has priority in the payment of dividends distribution, but does not give voting rights. The following table not only shows that both types belong to our database but also confirms that it consists of high liquid assets. The range of sectors imposed by our stocks' selection just reflects the diversification of Brazilian industry. Thus, the concentration on the basic materials' industry is not a surprise, but other important industries such as financial and utilities are represented as well.

Table 24: The list of stocks, number of transactions and transaction gap per stock

Stock	Total number of transactions (millions)	Sector	Average gap between transactions (in seconds)
Ambev PN (AMBV4)	1.49	Consumer	26.9
Bradesco PN (BBDC4)	6.00	Financial	6.7
Bradespar PN (BRAP4)	2.12	Financial	18.9
Banco do Brasil ON (BBAS3)	4.70	Financial	8.5
Cemig PN (CMIG4)	3.04	Utilities	13.1
Cia Siderúrgica Nacional ON (CSNA3)	4.36	Basic Materials	9.2
Cyrella ON (CYRE3)	3.69	Real State	10.8
Eletrobras PN (ELET6)	2.03	Utilities	19.6
Gafisa ON (GFAS3)	3.14	Real State	12.7
Gerdau PN (GGBR4)	6.23	Basic Materials	6.4
Petrobras PN (PETR4)	17.53	Basic Materials	2.3
Usiminas PN (USIM5)	4.91	Basic Materials	8.1
Cia Vale do Rio Doce (VALE5)	15.26	Basic Materials	2.6
OGX Petróleo ON (OGXP3)	3.29	Basic Materials	6.4
Itausa Investimentos ON (ITSA4)	5.22	Financial	7.6
Itau Unibanco Holding S.A. ON (ITUB4)	3.67	Financial	3.7
PDG Realty S.A. ON (PDGR3)	2.54	Real State	12.6
Hypermarcas ON (HYPE3)	0.98	Consumer	22.7
BMFBOVESPA S.A. ON (BVMF3)	6.01	Financial	3.2
Redecard ON (RDCD3)	2.58	Financial	10.9

Note: In parenthesis, the stock code at BMF&Bovespa.
ON – common share PN – preferred share.

Before constructing realized volatility estimates, the first decision concerns the sampling frequency. The choice of the optimal frequency involves a trade-off between microstructure issues and loss of information as we will discuss below. If we increase the sampling frequency, we bring to light microstructure problems, such as the bid-ask bounce and error measurement due to price discreteness. In this respect, Aït-Sahalia (2005) showed that, in the presence of microstructure noise, it is optimal to sample less frequently than it would otherwise. On the other hand, over decreasing the sampling frequency does not make sense in an intraday analysis. The 5-min sampling frequency is our choice as is the common practice in the realized measure literature, (Fleming et al (2003), Andersen et al (2000), among others), and also in stock market applied studies (Chiriac & Voev (2011), Golosnoy et al (2012), Andersen et al (2003), among others).

Once having chosen the 5-min frequency, the next step was to choose the proxy of our main variable of interest: the prices. As Roll (1984), the fundamental price is unobservable and its value lies somewhere between the bid and ask quotes. Mid-spread quotes and transaction prices share this characteristic and are the natural candidates. Using transaction data is appropriate only if the stock liquidity is big enough to minimize the need for interpolation. Say, for instance, that there are no deals nearby a 5-min interval. In this case, one must do some inference about the value at this point. Considering that the price remains unchanged or employing a weighted average, based on the distance between the time of the transaction and the 5-min interval, are simple and straightforward manners to over this problem. However, the error measurement associated with this choice cannot be neglected in some situations.

On the other hand, the advantage for the use of mid-spread is twofold. First of all, buy and sell orders are available on a higher frequency eliminating the interpolation step. Besides, it avoids the bid-ask bounce issue described by Roll (1984). In most applications from the literature, the transactions prices and information on spreads come in the same database registry. In our case, orders' data come separate from the transactions' data, so we needed to create an order book and, for each new transaction, update bid and ask information. However, the analysis of orders' data showed a great number of outliers, probably due to reporting errors. As Brownlees & Gallo (2006) note, the number of errors is proportional to the velocity of information and this is especially true in our case that involves tenths of millions registries for each stock. Excluding outliers, the next step is to define a rule to filter the remaining data. Considering a simple one[56], we verified a persistence of a great number of suspicious registries.

Thus, in terms of reliability, using transaction data is the best choice. Next, we got the prices at each 5-min interval, starting at 10:00 AM, local time, and ending at 17:00 PM[57]. After cleaning the database for outliers and treating simultaneous observations[58], we identified the transaction prices nearest to the 5-min grid. As all the stocks have high liquidity parameters, we considered that this price remains valid until the end of a given 5-min grid. We then first difference the log prices for all grids to obtain the 5-min returns. In Table 25, we can see that, although autocorrelations are very close to zero in most cases, they remain mostly negative until lag 5 probably due to residual microstructure noise.

Table 25: Autocorrelation of 5-min returns

Stock	Lag 1	Lag 2	Lag 5
Ambev PN (AMBV4)	-0.019	-0.025	-0.005
Bradesco PN (BBDC4)	-0.014	-0.010	0.006
Bradespar PN (BRAP4)	-0.013	-0.002	0.009
Banco do Brasil ON (BBAS3)	-0.018	-0.021	-0.004
Cemig PN (CMIG4)	-0.027	-0.027	0.007
Cia Siderúrgica Nacional ON (CSNA3)	-0.018	0.000	0.005
Cyrella ON (CYRE3)	-0.029	-0.006	0.001
Eletrobras PN (ELET6)	-0.015	-0.017	-0.004
Gafisa ON (GFAS3)	-0.026	-0.017	0.001
Gerdau PN (GGBR4)	-0.026	-0.002	0.007
Petrobras PN (PETR4)	0.000	0.002	0.005
Usiminas PN (USIM5)	-0.020	-0.016	0.012
Cia Vale do Rio Doce (VALE5)	-0.013	0.002	0.007
OGX Petróleo ON (OGXP3)	-0.046	-0.018	-0.004
Itausa Investimentos ON (ITSA4)	-0.013	-0.004	0.008
Itau Unibanco Holding S.A. ON (ITUB4)	-0.036	-0.010	-0.007
PDG Realty S.A. ON (PDGR3)	-0.047	-0.013	-0.016
Hypermarcas ON (HYPE3)	-0.026	-0.016	-0.021
BMFBOVESPA S.A. ON (BVMF3)	-0.019	-0.004	0.014
Redecard ON (RDCD3)	-0.031	-0.007	-0.007

[56] Exclusion of spreads superior to 0.2% of the last price and negative ones.

[57] Opening timing varied through the sample, and calculations were modified according to those changes.

[58] Due to trading report approximations, some transactions occurred at the same time. In these cases, we took the average value as a solution.

To calculate realized volatilities we refer to Liu, Patton & Sheppard (2013) who compared a great variety of realized measures in terms of forecasting accuracy and concluded that it is difficult to beat a simple 5-min RV measure, one without correction for microstructure or the use of tick-by-tick information. In this sense, RV is defined for each day t and stock i as:

$$RV_{i,t} = \sum_{i=1}^{T} r_{i,t}^2 \tag{3.3.1}$$

Where $r_{i,t}$ is the 5-min return and T is the number of 5-min intervals.

The covariance measures were estimated as below, for each day t and pair of stocks (i,j):

$$RCOV_{ij,t} = \sum_{i=1}^{T} r_{i,t} . r_{j,t} \tag{3.3.2}$$

Where $r_{i,t}$ and $r_{j,t}$ are the 5-min returns for stocks (i,j) and T is the number of 5-min intervals.

This measure is the covariance counterpart of the RV measure, without correction for microstructure and will be used in order to preserve the compatibility with the RV measure[59].

3.4.The model: Heterogeneous Auto-Regressive (HAR)

Before getting into the details of our model, it is interesting to discuss the desired properties of a volatility model. One stylized fact is that the distribution of returns departs from a normal distribution. As you can see in Table 26, this is especially true for all the stocks analyzed in the study in that all exhibit excess kurtosis and rejection of the null hypothesis of a Jarque-Bera test. A simulation exercise made by Corsi (2009) showed that we can recover this characteristic by applying a simple HAR model.

[59] The literature has provided a number of possibilities to correct for microstructure. McAleer & Medeiros (2008) described some of these methods that vary according to the assumptions regarding the noise structure. More recently, Corsi & Audrino (2012) propose a tick-by-tick approach.

Table 26: Summary statistic for daily returns

Stock	Returns * 100	(Standard deviation) * 100	Kurtosis	Jarque-Bera
Ambev PN (AMBV4)	0.01	2.66	7,98	Rejection of null hypothesis of normality
Bradesco PN (BBDC4)	0.06	2.75	7,64	
Bradespar PN (BRAP4)	0.01	3.08	6,58	
Banco do Brasil ON (BBAS3)	-0.01	4.00	8,85	
Cemig PN (CMIG4)	0.02	3.00	6,71	
Cia Siderúrgica Nacional ON (CSNA3)	0.02	259	5,04	
Cyrella ON (CYRE3)	0.01	3.91	7,49	
Eletrobras PN (ELET6)	0.08	3.17	8,87	
Gafisa ON (GFAS3)	0.01	2.25	7,52	
Gerdau PN (GGBR4)	0.07	2.98	7,50	
Petrobras PN (PETR4)	0.00	2.56	9,61	
Usiminas PN (USIM5)	0.04	2.87	8,44	
Cia Vale do Rio Doce (VALE5)	0.07	2.10	7,97	
OGX Petróleo ON (OGXP3)	0.03	0.042	6,54	
Itausa Investimentos ON (ITSA4)	0.04	0.027	9,94	
Itau Unibanco Holding S.A. ON (ITUB4)	0.02	0.018	5,66	
PDG Realty S.A. ON (PDGR3)	0.09	0.038	7,71	
Hypermarcas ON (HYPE3)	0.07	0.030	5,70	
BMFBOVESPA S.A. ON (BVMF3)	0.00	0.040	7,86	
Redecard ON (RDCD3)	-0.03	0.030	5,40	

Another stylized fact is that financial volatility returns are usually long memory processes in that large volatility shocks are not quickly forgotten. In ARCH and GARCH models, autocorrelation decreases exponentially when it should be a hyperbolic decay. In fact, our data suggests a very slow decay of autocorrelation in square daily returns, up to lag 100, or approximately 5 months.

Table 27: Autocorrelation of squared returns

Stock	Lag 1	Lag 20	Lag 100
Ambev PN (AMBV4)	0.22	0.28	0.01
Bradesco PN (BBDC4)	0.13	0.10	0.03
Bradespar PN (BRAP4)	0.06	0.08	0.04
Banco do Brasil ON (BBAS3)	0.29	0.18	0.06
Cemig PN (CMIG4)	0.22	0.16	0.07
Cia Siderúrgica Nacional ON (CSNA3)	0.18	0.07	-0.03
Cyrella ON (CYRE3)	0.18	0.15	0.01
Eletrobras PN (ELET6)	0.28	0.16	0.04
Gafisa ON (GFAS3)	0.05	0.03	0.02
Gerdau PN (GGBR4)	0.11	0.10	0.05
Petrobras PN (PETR4)	0.16	0.08	0.04
Usiminas PN (USIM5)	0.18	0.06	0.02
Cia Vale do Rio Doce (VALE5)	0.10	0.09	0.03
OGX Petróleo ON (OGXP3)	0.33	0.24	0.01
Itausa Investimentos ON (ITSA4)	0.18	0.12	-0.01
Itau Unibanco Holding S.A. ON (ITUB4)	0.12	0.03	-0.01
PDG Realty S.A. ON (PDGR3)	0.19	0.22	-0.02
Hypermarcas ON (HYPE3)	0.08	0.12	-0.01
BMFBOVESPA S.A. ON (BVMF3)	0.36	0.31	0.03
Redecard ON (RDCD3)	0.17	0.10	0.03

In this regard, Corsi (2009) proposes an additive model that is simple to estimate and able to replicate the long memory characteristic of volatility processes: the Heterogeneous Auto-Regressive (HAR). Fractional difference operators (FIGARCH and ARFIMA models) share the same long memory property of HAR processes. However, not only it lacks of flexibility and economic interpretation, but also requires a great amount of data to work properly.

The HAR model is supported by economic theory and, thus, adds the advantage of having economic interpretation. The Heterogeneous Market Hypothesis was first presented by Muller et al (1997). The idea behind the theory is that if all traders were the same, prices should converge immediately to its real price and the correlation between market presence and volatility should be negative. However, this is not what happens in practice and it is due to the heterogeneity of agents that execute transactions in different market situations and trading frequencies. Besides, they are motivated by different set of factors such as endowment, degree of information, prior belief, as. Market makers and active investors, for instance, have a more immediate trading horizon and focus on short term results. On the other hand, there are portfolio managers (financial and non-financial) as well as investors which focus on medium and long term prospects, rebalancing their positions less frequently. These characteristics make room for a model with short, medium and long term components such as HAR.

3.4.1.The univariate case

We will provide the main features of the model that departs from the framework from Corsi (2009) and Corsi & Reno (2012) with two exogenous variable included and additional features to allow for the implementation of a multivariate setting. The basis for the construction of the HAR models is LeBaron (2001), which shows that the long memory property can be reproduced by a sum of three different linear processes. In both articles, the agents' heterogeneity is represented by a few time scales (day, week and month). For each level of the cascade, we define an unobservable component, a partial volatility measure ($\tilde{\sigma}_t^{(d)}, \tilde{\sigma}_t^{(w)}, \tilde{\sigma}_t^{(m)}$), as a function of the past observation of the realized volatility and the expectation of the partial volatility of the next time scale. This last term accounts for the asymmetric propagation of volatility which incorporates a stylized fact that longer term volatility have stronger influence on

short term ones than the inverse. In the framework of Heterogeneous Market Hypothesis, it is very reasonable to say that short term traders are more interested in the longer term volatility than the other way round. Thus, for the longer time span (monthly, in our case), only the past observation remains. Accordingly, the model can be written as:

$$\tilde{\sigma}_{t+1d}^{(d)} = \alpha_d + \beta^{(d)} RV_t^{(d)} + \gamma^{(d)} E_t \tilde{\sigma}_{t+1w}^{(w)} + \omega_{t+1d}^{(d)} \quad (3.4.1.1)$$

$$\tilde{\sigma}_{t+1w}^{(w)} = \alpha_w + \beta^{(w)} RV_t^{(w)} + \gamma^{(w)} E_t \tilde{\sigma}_{t+1m}^{(m)} + \omega_{t+1w}^{(w)} \quad (3.4.1.2)$$

$$\tilde{\sigma}_{t+1m}^{(m)} = \alpha_m + \beta^{(m)} RV_t^{(m)} + \omega_{t+1m}^{(m)} \quad (3.4.1.3)$$

Where $RV_t^{(d)}$, $RV_t^{(w)}$and $RV_t^{(m)}$ stands for daily, weekly and monthly realized measures, respectively.

Over longer time horizons, realized volatility is defined as an average of daily past realized volatilities over the time scale:

$$RV_t^{(x)} = \frac{1}{x} \left(RV_{t-1d}^{(d)} + RV_{t-2d}^{(d)} + \cdots RV_{t-xd}^{(d)}\right) \quad (3.4.1.4)$$

Where x is the number of days.

A single variable setting only requires an adequate errors' structure to ensure positive definiteness. Alternatively, one can use can use logarithms instead of the original variables. As we will see, extending this framework to a multivariate setting will require additional steps.

Besides, the return process is a function of the highest frequency component ($r_t = \sigma_t^{(d)}.\varepsilon_t$). By recursive substitution, we reach the following simple specification for the cascade model:

$$\tilde{\sigma}_{t+1d}^{(d)} = \alpha + \beta^{(d)} RV_t^{(d)} + \beta^{(w)} RV_t^{(w)} + \beta^{(m)} RV_t^{(m)} + \omega_{t+1d}^{(d)} \quad (3.4.1.5)$$

By assuming that measurement errors ($\omega_{t+1d}^{(d)}$, $\omega_{t+1d}^{(w)}$, $\omega_{t+1d}^{(m)}$) are contemporaneously and serially independent zero mean variates, the partial volatility measure can be substituted by the realized volatility directly into equation (3.4.1.5):

$$RV_{t+1d}^{(d)} = \alpha + \beta^{(d)} RV_t^{(d)} + \beta^{(w)} RV_t^{(w)} + \beta^{(m)} RV_t^{(m)} + \epsilon_{t+1d}^{(d)} \quad (3.4.1.6)$$

3.4.2.The extension to the multivariate case

The first concern when working in a multivariate setting is ensuring the positive definiteness of the covariance matrix. Hence, we need to decompose the time-varying covariance matrix in such a way to guarantee this property. Chiriac & Voev (2011) proposes a Choleski factorization that ensures. However, this option was rejected due to the fact that the results were dependent on the ordering of the assets, probably due to the larger number of assets we included in our work (twenty instead of six). Bauer & Vorkink (2011) offer a more suitable solution for the decomposition. The method takes advantage of some useful properties of matrix exponential and logarithmic functions.

First of all, taking the matrix logarithm of a real, positive definite matrix results in a real, symmetric matrix. Thus, consider the covariance matrix Σ of dimension 20x20, which is symmetric and positive definite and apply the logarithm function[60].

$$A_t = logm(\Sigma_t) \qquad (3.4.2.1)$$

Where the *logm* function computes the matrix logarithm using the algorithm proposed by Higham & Davies (2003).

Note that this transformation involves a rotation in the original elements, which are not represented one by one in the new space, the log-space. It yields a real, symmetric matrix which will be used for the purpose of forecasting. This is done by stacking the columns of the upper portion of matrix A_t one under another, into a single column.

$$a_t^{(i)} = vech\ (A_t^{(i)}) \qquad (3.4.2.2)$$

Where the vector a_t has 210 elements and *vech* is the function that creates a column vector whose elements are the stacked columns of the upper portion of a given matrix. The index (i) refers to daily (d), weekly (w) and monthly (m) covariance matrices.

To estimate the conditional variance we use different specifications for the multivariate HAR model. As we aim a good out-of-sample fitness, we need to control the degree of parameterization. If, for each equation, we included the information from all the other assets we would have at least 12 additional regressors at each forecast. So, we need to wrap up cross-asset information into few variables. Applying a Principal Component Analysis, we can consolidate into as many variables as we want. The first component already accounts for more than 70% of the variance of the realized volatilities and it suffices for the purpose of forecasting. We will call this the market volatility (MV).

As Brazilian market is notoriously affected by external factors, another additional feature is to include a proxy for the volatility of the US market. The VIX index is a measure of the implied volatility of S&P 500 traded at Chicago Board Options Exchange Market. For the sake of simplicity, we will use only its last observation, avoiding introducing another cascade variable. Besides, it is fair to say that distant external volatility horizons are already absorbed by the domestic realized measures.

In what follows, we present the final specification that will be tested in equation (3.4.2.3). To Corsi's HAR specification, we include the daily VIX index and market volatility (MV) as exogenous variables.

$$a_{t+1d}^{(d)} = \alpha + \beta^{(d)} a_t^{(d)} + \beta^{(w)} a_t^{(w)} + \beta^{(m)} a_t^{(m)} + \delta^{(d)} MV_t^{(d)} + \delta^{(w)} MV_t^{(w)} + \delta^{(m)} MV_t^{(m)} + \theta.\log(VIX_t) + \epsilon_{t+1d}^{(d)}$$
(3.4.2.3)

Finally, to obtain the forecasted value in the original parameter space, we apply the exponential matrix function (*expm*) to the covariance matrix in the log-space, a procedure that preserves its positive definiteness.

$$\Sigma_{t+1} = expm(A_{t+1}) \qquad (3.4.2.4)$$

Where A_{t+1} is the symmetric matrix reconstructed by the elements of the forecasted column vector a_{t+1}.

[60] Computing the autocorrelation functions, we conclude that the long memory is preserved even after the logarithmic transformation.

The function *expm* in Matlab performs the following mathematical operation: $e^{A_t} = \sum_{k=0}^{\infty} \frac{1}{k!} {A_t}^k$, following the algorithm proposed by Higham (2005). As a matter of fact, the scaling and squaring method in Higham (2005) is one of the preferable ones according to Moler & Loan (2003).

Model (3.4.2.3) is a multivariate version of the HAR model using realized volatility and will be referred as MHAR-RV in the remainder of the paper.

3.4.3.Out-of-sample performance

Now we turn our attention to obtain forecasting estimates for the next-period realized volatility. The time horizon has been defined as one day. Ideally, we want that realizations of the forecasting error to be unpredictable. Andersen et al (2006) proposes a natural diagnostic of this property with a simple linear regression under a general loss function:

$$E_t\left[\frac{\partial L(y_{t+1}, \widehat{y_{t+1|t}})}{\partial \hat{y}}\right] = a + b' x_t + \varepsilon_{t+1} \qquad (3.4.3.1)$$

Where the regressor x_t can be defined arbitrarily.

This regression can be estimated by OLS taking into account the heteroskedasticity of errors. A well calibrated forecasting method should result in *a=b=0*. If we take the loss function as quadratic and x_t as the forecasted volatility, we can rewrite equation (3.4.3.1) as:

$$\sigma^2_{t:t+1} = a + (b+1)\widehat{\sigma^2_{t:t+1}} + +\varepsilon_{t+1} \qquad (3.4.3.2)$$

Realized volatility allows us to compute the *ex-post* measure ($\sigma^2_{t:t+1}$) and our multivariate HAR-RV models will generate different measures of the *ex-ant* one ($\widehat{\sigma^2_{t:t+1}}$). This is the so-called Mincer-Zarnowitz regressions which were applied to our realized variance/covariance measures.

As you can see in Table 28, *'b'* coefficients are significantly equal to zero for the majority of the stocks. Also, it should be noted that there is a systematic error as implied by the presence of a nonzero *'a'* coefficient value. Stocks with the lowest liquidity levels showed the poorest fits suggesting that it can be an important driver to the models' performance.

Table 28: Mincer-Zarnowitz regression for variances (Window 150)

Null a=0	Null b=0	$Mean\ R^2$
Rejected (20)	Not rejected (17)	0.55

Note: In parenthesis, the number of stocks in which the null hypothesis was not rejected.

With respect to covariances, we will focus on the forecasting regression relative to PETR4, the most representative stock in the database. Again, *'b'* coefficients are significantly equal to zero and we accounted for the presence of a systematic error. Lower R^2 figures show that variance fit is superior to covariance one. The difference can be attributed to the fact that our MHAR-RV modelo does not allow for potential divergences in terms of long memory properties between variance and covariances.

Table 29: Mincer-Zarnowitz regression for PETR4 covariances

Null a=0	Null b=0	$Mean\ R^2$
Rejected (20)	Not rejected (18)	0.10

Note: In parenthesis, the number of stocks in which the null hypothesis was not rejected.

In Brazil, Wink Junior & Valls Pereira (2012) analyze out-of-sample realized volatility forecasting performance of five Brazilian stocks. The authors conclude that there were no significant different between Corsi's HAR-RV and Mixed Data Sampling (MIDAS-RV), developed by Ghysels et al (2004).

3.5.The comparison of economic value

Besides forecasting, conditional covariance estimation will be valuable for the purpose of portfolio optimization. According to its investment horizons, agents rebalance its portfolios in the face of events or trends that redefine the perception of each stock parameter, especially mean and variance expected returns. A multivariate framework is particularly important as we are usually dealing with multiple assets and its comovements need to be taken into account. The set up of the optimization problem depends on what one wants to test.

Fleming et al (2001) defined an optimization problem based on a volatility timing strategy that is well suited to our subject of interest, i.e., the analysis of covariance measures and model´s estimation. The authors compared a daily rebalanced portfolio with a static one in terms of economic utility. This methodology seeks to estimate how many basic points a mean-variance investor would be willing to pay to switch strategies. Fleming et al (2003) did the same kind of analysis just switching from a GARCH estimation procedure to a model based on realized volatility.

We will compare our specification of the MHAR-RV model two traditional models, namely Multivariate GARCH (MVGARCH) and Exponential Weighted Moving Average (EWMA). EWMA is the most common approach to calculate time-varying covariance matrices. As defined by Riskmetrics, the daily volatility is calculated as follows:

$$\widehat{\Omega_t} = \lambda \sum_{i=1}^{N} (1-\lambda)^{i-1} Y_t Y_t{}' \qquad (3.5.1)$$

Where Y_t is the matrix of daily returns. Although the parameter λ is defined arbitrarily, Riskmetrics recommends using 0.6 for stocks. The idea is to assign higher values to most recent observations.

The MVGARCH calculation builds on the work of Engle (2000) to deal with large conditional covariance matrices. Decomposing the conditional covariance matrix as follows:

$$\Omega_{t|t-1} = \mathrm{D}_{t|t-1} \Gamma_{t|t-1} \mathrm{D}_{t|t-1} \qquad (3.5.2)$$

Bollerslev (1990) assumes that the temporal variation in the covariances is driven only by standard deviations, making $\Gamma_{t|t-1=}\Gamma$, for every t. Engle's DCC (dynamic conditional correlation) model assumes that the correlation process follows a GARCH (1,1) process, avoiding the oversimplification from Bollerslev's model.

Consider an investor that follows a volatility timing strategy, where he wants to minimize volatility subject to a target return (μ_p). Let Σ_t be the 20x20 conditional covariance matrix, R_{t+1} and $\mu=E(R_{t+1})$ be a 20 x1 vector of risk asset returns and its expectation. Let also be the risk-free asset $R_{f,t}$ and w_t a 20x1 matrix of the portfolio weights.

$$\min_{w_t} w_t'.\Sigma_t.w_t$$

$$s.t. w_t'.\mu + (1 - w_t'.\mathbf{1}).\boldsymbol{R_{f,t}} = \mu_p \qquad (3.5.3)$$

Concerning the risk-free asset, some remarks must be made about the Brazilian economy. First of all, the choice of the reference rate is not free of controversy. As we do not have a highly active secondary market for federal government bonds, it is necessary to choose a reference for the short-term rate. The 30-day swap, a futures contract traded at BVM&F, is a

market reference for the evolution of short-term interest rates. The interbank deposit rate (CDI – Certificado de Depósito Interbancário) would be another option. However, this measure is more sensitive to market conditions that do not affect the fundamentals of a riskless asset. Besides, note that the variable was indexed by time due to the fact that the prime interest rate varied considerably over the sample period. This is in odds with to the constant value assumption, as of Fleming et al (2001,2003). Allowing for short selling, the solution for the minimization problem results in the following equation for portfolio weights.

$$w_t = \frac{(\mu_p - R_{f,t}).\Sigma_t^{-1}.(\mu - R_{f,t}.\mathbf{1})}{(\mu - R_{f,t}.\mathbf{1}).\Sigma_t^{-1}.(\mu - R_{f,t}.\mathbf{1})} \qquad (3.5.4)$$

The computation of portfolio returns generated by (3.5.4) take into account trading costs, which may be a relevant portion of high frequency strategies. In this respect, BMF&Bovespa provides information on trading and post-trading costs to day-trade operations. Since such costs vary according to trading volume, we will consider the highest-cost scenario (0.025% per trading), which corresponds to investments up to $ 4 million and $ 20 million Brazilian reais, respectively to individual and institutional investors.

According to Fleming et al (2001), volatility timing strategy benefits from smoother conditional covariance matrix values. In Annex C, Graphs 10 to 12 show the comparison between different volatility measures for the most liquid stocks of our database (Vale and Petrobras) and their covariance. Although volatility series move together for the most part of the sampling period, MHAR-RV diverges in the period surrounding the 2008's financial crisis and also around the second trimester of 2007.

Now consider the rationale for the evaluation of the economic value. The choice of the utility is arbitrary but should be consistent with the problem at hand. In this sense, in an optimization problem with first and second moments involved, a quadratic utility is a natural candidate. Moreover, it can be viewed as a second order approximation of any investor´s utility. From this point, we will follow the utility format proposed by Fleming et al (2001),where W_{t+1} is the investor wealth at t+1 and *a* is his absolute risk aversion.

$$U(W_{t+1}) = W_t.R_{p,t+1} - \frac{aW_t^2}{2}.R_{p,t+1}^2 \qquad (3.5.5)$$

Where $R_{p,t+1}$ is the portfolio return, including the risk-free asset.

If we hold $a.W_t$ constant, this is equivalent to setting the relative risk aversion constant (γ). It allows us to calculate the average utility as follows.

$$\bar{U}(.) = W_0.(\sum_{t=0}^{T-1} R_{p,t+1} - \frac{\gamma}{2.(1+\gamma)}.R_{p,t+1}^2) \qquad (3.5.6)$$

Where W_0 is the initial wealth.

The value of volatility timing is calculated by equating the average utility of two alternative portfolios. This equality is obtained by including an operator Δ in one side of the equation and, then, calculating the value that equates both sides (the result of a second order polynomial).

$$\sum_{t=0}^{T-1}(R_{1p,t+1} - \Delta) - \frac{\gamma}{2.(1+\gamma)}.(R_{1p,t+1} - \Delta)^2 = \sum_{t=0}^{T-1} R_{2p,t+1} - \frac{\gamma}{2.(1+\gamma)}.R_{2p,t+1}^2 \qquad (3.5.7)$$

If asset 1 is the MHAR-RV portfolio, the value of Δ can be interpreted as its economic gain or performance fee associated to switching to an alternative portfolio based on a different measure of volatility (asset 2). It resembles the concept of certainty equivalent as the value of Δ can also be interpreted as the risk premium associated with the choice of a strategy based on realized measures.

3.6.Results

Note that the implementation steps towards the economic gain value require some arbitrary choices. Therefore, we propose a baseline scenario which will be explored in detail and we will additionally introduce changes one at a time, thus enabling us to isolate the effect of each choice and confirm if they are not neutral to the results. Regarding the volatility forecasting procedures, for instance, each econometric approach requires a minimum window length for the estimation in order to avoid small sample bias. In this sense, our baseline scenario considers a lag length equal to 150 trading days, equivalent to approximately 7 months.

Back to equations (3.5.5) and (3.5.6), it becomes clear that large levels of risk aversion impose a penalty on large variations of the portfolio returns. Using different utility specification, Issler & Piqueira (2000) found that investors in Brazil are more risk averse than in US. However, their estimated results did not indicate an unambiguous value for this parameter. Consequently, concerning the investors´ utility, it is more realistic to start with an average risk-averse investor (risk aversion parameter equal to three) and we will treat extreme investors (risk aversion parameter equal to one and ten) as a special case in Section 3.6.4. For the same reason, we opted for a daily investment horizon to account for more active traders which rebalance their portfolio at higher frequencies.

In the minimization problem (3.5.3), you can see that there are no restrictions on short selling. Short selling is a key tool for hedging purposes and many financial economists believe that it is necessary to prevent prices from reflecting only the views of the most optimistic investors in the market. Hence, a decrease in return volatility is the expected effect of such a strategy with higher weights on the risk-free asset, while the excess return is obtained through the alternation of long and short positions. The size of the stock lending market in Brazil can be used as a proxy to infer the frequency of short selling operations. According to Chague et al (2013), stock lending experienced a substantial increase, from $ 1.56 billion in 2000 to $ 436.3 billion dollars in 2011. More importantly, almost 300 stocks were involved in at least one lending operation in 2011, endorsing the reference scenario where short selling is allowed. In this respect, we will also perform a robustness check with no short selling allowed, where we expect not only the weight on the risky assets to increase but return volatility as well.

In asset pricing, estimation risk refers to investor's uncertainty about the parameters of the return, playing a major role in our optimization problem. As estimation risk can offset or even overestimate possible economic gains associated with our reference portfolio, MHAR-RV, how should we deal with this issue? We will split economic gain analysis according to the level of control over estimation risk. First, we consider a situation of minor estimation risk that is controlled by using ex-post information, i.e., the unconditional expected returns are applied through the whole sample. As the riskless asset changes its price, risky assets tend to move accordingly. In other words, considering R_f conditional on time is inconsistent with an unconditional μ. In this sense, we considered a second level of estimation risk that takes short term expectations into account by calculating expected returns based on the conditional mean. We will also consider a third situation, where estimation risk is accounted for by bootstrapping each return series.

Before proceeding, we should remind that we do not want to find the best method to forecast returns as we know all the difficulties inherent in this task. However, we believe that changing this assumption and amplifying the scope of the study allows us to make more sound conclusions about it. The economic gains and all returns and interest rates are expressed in an annualized basis.

3.6.1.Controlling estimation risk

3.6.1.1.Unconditional mean

This is the so called “no estimation risk” situation described by Fleming et al (2001). From Table 30, we can see that MHAR-RV economic gains are positively correlated with target return levels. For a target level of 17.5% and short selling is allowed, an investor would be willing to pay 30.9 and 109.3 basis points to switch from a portfolio based on EWMA and MVGARCH, respectively, to a portfolio based on MHAR-RV forecasts. Fleming et al (2003) made a similar comparison and found a performance fee of 21.9 basis points[61] between a rolling RV estimator and a EWMA approach. In spite of the fact that the results are not directly comparable[62], the fact that they are in the same order of magnitude even when a greater number of assets is included in the multivariate setting should be seen as an indication of the benefits of realized volatility.

For low target levels, realized volatility did not have a superior performance, probably due to the proximity between the target level and risk-free levels in the Brazilian economy (see Graph 13 in the Annex C) leading to portfolio weights that reduce the value of volatility timing. In fact, the optimization problem induces a self-financed portfolio, with near-unity risk-free portfolio weights and alternate long and short positions in the risky assets of low absolute value, depending on the expected returns.

Table 30: Economic gain (in basis points) between the reference and alternative portfolios (Size of the Estimation Window 150)

The database covers the period from February 2006 to January 2011 for the twenty stocks listed in Table 24. Portfolio weights were computed according to the volatility-timing strategy described in equation (3.5.4), allowing for short selling and equaling the expected return for each stock to its unconditional mean. The forecasted values of realized volatility are based on equation (3.4.2.3). Utility gains were then computed as in equation (3.5.7), with γ=3. The size of the estimation window is 150 trading days.

Reference Portfolio	Alternative portfolio	Target return		
		μ_p=12.5%	μ_p=15.0%	μ_p=17.5%
MHAR-RV	EWMA	-68.6	18.8	30.9
	MVGARCH	-11.8	49.3	109.3

With Table 31, we are able to take a closer look at the results in term of weights and returns. As expected, increasing values for the target return leads to higher risk levels, as measured by the return´s standard deviation. Moreover, weights on the risk-free asset are near to 100% in all instances. To account for risk reward, Sharpe Ratio figures show that MHAR-RV portfolio is superior for target levels of 15.0% and 17.5%, but this advantage is not strong at the 12.5% level just as the economic gain analysis reveals. Note also that average portfolio returns are an increasing function of the target return confirming the efficacy of our strategy to control for estimation risk, but we will see that this superior performance is only promising as long as we use ex-post information, that is, if one has informational advantage.

[61] With no correction for microstructure and inclusion of overnight returns in the volatility measurement procedure and γ=1.

[62] There are differences in the RV forecasting model and in the level of risk of the assets involved. The target return is 10% while the risk-free level is 6% a year and assumed to be constant over the sample period.

Table 31: Descriptive statistics for portfolio returns

Statistics are derived from the daily portfolio returns, constructed with the weights generated by the volatility-timing strategy (3.5.4), in an annualized basis. Short selling is allowed and expected return for each stock is equal to its unconditional mean. The size of the estimation window is 150 trading days.

Target return=12.5% a.y.			
	MHAR-RV	EWMA	MVGARCH
Average Return	12.19%	12.29%	12.08%
Standard Deviation	1.71%	1.88%	1.77%
Sharpe Ratio	-0.18	-0.12	-0.24
Weight on Riskfree asset	100.0%	99.8%	99.8%
Target return=15.0% a.y.			
	MHAR-RV	EWMA	MVGARCH
Average Return	13.87%	13.20%	13.86%
Standard Deviation	3.48%	3.76%	3.44%
Sharpe Ratio	-0.32	-0.48	-0.33
Weight on Riskfree asset	101.7%	99.7%	99.9%
Target return=17.5% a.y.			
	MHAR-RV	EWMA	MVGARCH
Average Return	16.87%	14.04%	15.49%
Standard Deviation	5.65%	6.11%	5.56%
Sharpe Ratio	-0.11	-0.57	-0.36
Weight on Riskfree asset	103.0%	99.4%	99.9%

3.6.2.Conditional mean

Using the conditional mean as the parameter for the estimation of expected returns, we aim to progressively increase the exposure to estimation risk. With that in mind, we calculated the conditional mean as an annualized average return of the past six-months, or 120 commercial days approximately. Additionally, to avoid excess variability, we assume that the investors updated expected returns on a monthly basis, i.e., the conditional mean remained constant over the next 20 days.

Comparing to the “no estimation risk”, Table 32 shows that economic gains not only increased substantially but are positive in all comparisons. Performance fees remains positively correlated to the target return and gains are superior when EWMA is the alternative portfolio. Economic gains range from 13.0 to 152.1 basis points taking MVGARCH as the alternative portfolio.

Table 32: Economic gain (in basis points) between the reference and alternative portfolios

The database covers the period from February 2006 to January 2011 for the twenty stocks listed in Table 24. Portfolio weights were computed according to the volatility-timing strategy described in equation (3.5.4), allowing for short selling and equaling the expected return for each stock to its conditional mean. The forecasted values of realized volatility are based on equation (3.4.2.3). Utility gains were then computed as in equation (3.5.7), with γ=3. The size of the estimation window is 150 trading days.

Reference Portfolio	Alternative Portfolio	Target return		
		μ_p=12.5%	μ_p=15.0%	μ_p=17.5%
MHAR-RV	EWMA	19.4	125.9	231.1
	MVGARCH	13.0	83.1	152.1

Turning to Table 33, we are able to evaluate the dramatic effect of estimation risk on portfolio returns given that volatility timing strategies are not able to deliver returns that are even close to the target, except when target returns are close to the risk-free rate. Although return increases in response to growing risk levels, it does so by small amounts in contrast to the “no estimation risk” situation. The risk-free asset maintains a high share in portfolio composition and the poor results can be attributed to the failure of conditional mean as a viable return forecast. Moreover, average returns lose the positive association with target returns, producing additional

evidence of the fundamental role of estimation risk in the outcome of the volatility-timing strategy.

Table 33: Descriptive statistics for portfolio returns

Statistics are derived from the daily portfolio returns, constructed with the weights generated by the volatility-timing strategy (3.5.4), in an annualized basis. Short selling is allowed and expected return for each stock is equal to its conditional mean. The size of the estimation window is 150 trading days.

Target return=12.5% a.y.			
	MHAR-RV	EWMA	MVGARCH
Average Return	10.78%	10.57%	10.64%
Standard Deviation	0.62%	0.64%	0.57%
Sharpe Ratio	-2.77	-3.02	-3.26
Weight on Riskfree asset	99.5%	99.8%	99.8%
Target return=15.0% a.y.			
	MHAR-RV	EWMA	MVGARCH
Average Return	10.59%	9.20%	9.66%
Standard Deviation	1.23%	1.27%	1.13%
Sharpe Ratio	-3.59	-4.57	-4.73
Weight on Riskfree asset	98.5%	99.5%	99.4%
Target return=17.5% a.y.			
	MHAR-RV	EWMA	MVGARCH
Average Return	10.41%	7.89%	8.78%
Standard Deviation	2.03%	2.06%	1.84%
Sharpe Ratio	-3.49	-4.67	-4.74
Weight on Riskfree asset	97.4%	99.2%	98.9%

3.6.3.Bootstrap

In order to obtain comparable results, we performed a simulation approach similar to the one employed by Fleming et al (2001). For each asset, we first generated a bootstrapped series of 2000 observations with replacement. Then, we calculated the average return of the first 500 observations and executed the same steps for 1000 times. From Table 34, we conclude that estimation risk offsets economic gains associated with our realized volatility measure. Although performance fees are in general positive on average, standard deviations are too large at a statistical viewpoint. While economic gains increase with the target level, the same goes for the standard deviation figures.

Table 34: Average economic gain (in basis points) between the reference and alternative portfolios

The database covers the period from February 2006 to January 2011 for the twenty stocks listed in Table 24. Portfolio weights were computed according to the volatility-timing strategy described in equation (3.5.4), allowing for short selling and equaling the expected return for each stock to its bootstrapped mean. The forecasted values of realized volatility are based on equation (3.4.2.3). Utility gains were then computed as in equation (3.5.7), with γ=3. The size of the estimation window is 150 trading days. Standard deviation in parenthesis.

Reference Portfolio	Alternative portfolio	Short selling allowed		
		μ_p=12.5%	μ_p=15.0%	μ_p=17.5%
MHAR-RV	EWMA	-19.6 (66.9)	0,5 (61.5)	3.5 (66.5)
	MVGARCH	-100.4 (201.7)	9.2 (220.5)	52.4 (223.0)

A closer look at the behavior of returns and weights show that average returns are stable over different target levels and not too far from the average risk-free rate (11.7% a.y.). Thus, under different return scenarios provided by our bootstrap simulation, volatility timing strategy is only able to incorporate a small premium over the risk-free rate on average. When short selling is restricted, there is no compensation for risk as returns do not rise as standard deviations increase.

Table 35: Descriptive statistics for portfolio returns

Statistics are derived from the daily portfolio returns, constructed with the weights generated by the volatility-timing strategy (3.5.4), in an annualized basis. Short selling is allowed and expected return for each stock is equal to its bootstrapped mean. The size of the estimation window is 150 trading days.

Target return=12.5% a.y.			
	MHAR-RV	EWMA	MVGARCH
Average Return	12.15%	11.83%	12.24%
Standard Deviation	1.23%	0.95%	1.02%
Sharpe Ratio	-0.28	-0.71	-0.25
Weight on Riskfree asset	101.0%	100.1%	100.3%
Target return=15.0% a.y.			
	MHAR-RV	EWMA	MVGARCH
Average Return	11.95%	11.99%	11.86%
Standard Deviation	1.14%	0.98%	0.97%
Sharpe Ratio	-2.67	-3.07	-3.24
Weight on Riskfree asset	100.7%	97.9%	97.5%
Target return=17.5% a.y.			
	MHAR-RV	EWMA	MVGARCH
Average Return	12.26%	12.27%	12.03%
Standard Deviation	1.28%	1.26%	1.05%
Sharpe Ratio	-4.09	-4.15	-5.29
Weight on Riskfree asset	100.0%	100.0%	100.0%

3.6.4.Additional Robustness checks

In an attempt to isolate the effect of the different volatility measures in a volatility-timing strategy, all robustness checks will consider the “no estimation risk” case, setting aside the issue of the role of expected returns in the optimization problem. So far, out-of-sample forecasts have been obtained with an estimation window of 150 days. As you can see in Table 36, results are robust to increasing window sizes as long as our first insights did not change. Economic gains are still positively related to target returns. The only noticeable change is the relative improvement of MVGARCH-based portfolios relative to the EWMA ones, suggesting that MVGARCH performs better for larger estimation windows.

Table 36: Economic gain (in basis points) between the reference and alternative portfolios

The database covers the period from February 2006 to January 2011 for the twenty stocks listed in Table 24. Portfolio weights were computed according to the volatility-timing strategy described in equation (3.5.4), allowing for short selling and equaling the expected return for each stock to its unconditional mean. The forecasted values of realized volatility are based on equation (3.4.2.3). Utility gains were then computed as in equation (3.5.7), with γ=3. Two different estimation window were used (200 and 250 trading days).

Reference Portfolio	Alternative Portfolio	Target return		
		μ_p=12.5%	μ_p=15.0%	μ_p=17.5%
Window Size= 200				
MHAR-RV	EWMA	-39.8	5.1	50.1
	MVGARCH	-18.0	10.1	37.5
Window Size= 250				
MHAR-RV	EWMA	-12.0	51.0	114.0
	MVGARCH	2.9	39.5	74.9

Recall that, to the basic structure of a HAR model, we included two exogenous variables: VIX and a proxy for the domestic market volatility. We wonder if economic gains are a consequence of a more complex MHAR-RV setting than EWMA and GARCH models. In Table 37, we computed the economic gain with a basic HAR without exogenous variables in the “no

estimation risk" case and, again, the relation between target levels and economic gains is positive. Despite the fact that the performance at the lowest target level (12.5%) is inferior, when we compare all instances of Table 30, results are similar and sometimes mixed. Hence, we can state that the realized volatility gains cannot be attributed to our model specification provided that overall conclusions are robust to it. Remember that the inclusion of exogenous variables aimed at adapting the model to an emerging country environment. The results, thus, show that such adaptations do not improve the volatility-timing strategy based on realized measures.

Table 37: Economic gain (in basis points) between the reference and alternative portfolios

The database covers the period from February 2006 to January 2011 for the twenty stocks listed in Table 24. Portfolio weights were computed according to the volatility-timing strategy described in equation (3.5.4), allowing for short selling and equaling the expected return for each stock to its unconditional mean. The forecasted values of realized volatility are based on a basic HAR specification, with no exogenous variables. Utility gains were then computed as in equation (3.5.7), with γ=3. Estimation window is equal to 150 trading days.

Reference Portfolio	Alternative portfolio	Short selling allowed		
		μ_p=12.5%	μ_p=15.0%	μ_p=17.5%
MHAR-RV	EWMA	-49.4	8.8	66.8
	MVGARCH	7.5	77.1	145.4

The introduction of a short selling restriction comes as a natural robustness check as we expect a huge change in portfolio composition, with substantial lower weights of the risk-free asset. It happens to be the case that, when the target return is 17.5%, the risk-free asset responds for less than 30% of portfolio composition irrespective of the volatility measure used. Besides reducing economic gains, utility gains and target returns lose the positive association verified in previous results.

Table 38: Economic gain (in basis points) between the reference and alternative portfolios with short selling restrictions

The database covers the period from February 2006 to January 2011 for the twenty stocks listed in Table 24. Portfolio weights were computed according to the volatility-timing strategy described in equation (3.5.4), with no short selling and equaling the expected return for each stock to its unconditional mean. The forecasted values of realized volatility are based on equation (3.4.2.3). Utility gains were then computed as in equation (3.5.7), with γ=3. Estimation window is equal to 150 trading days.

Reference Portfolio	Alternative portfolio	Target return		
		μ_p=12.5%	μ_p=15.0%	μ_p=17.5%
MHAR-RV	EWMA	0.9	36.3	-47.6
	MVGARCH	-20.1	-30.4	-166.0

In the reference case, investors' relative risk aversion (γ) has been set to 3. When γ alternates between extreme cases (1 and 10), the investor will impose lower (γ=1) or higher (γ=10) penalties over large variations in volatility forecasts but we cannot anticipate the results' profile since γ impacts all the coefficients of the second degree equation (3.5.7). As we can see in the following table, MHAR-RV economic gains are positively related to target levels and no marked changes are present, except concerning the relative performance between EWMA and MVGARCH.

Table 39: Economic gain (in basis points) between the reference and alternative portfolios

The database covers the period from February 2006 to January 2011 for the twenty stocks listed in Table 24. Portfolio weights were computed according to the volatility-timing strategy described in equation (3.5.4), allowing for short selling and equaling the expected return for each stock to its unconditional mean. The forecasted values of realized volatility are based on equation (3.4.2.3). Utility gains were then computed as in equation (3.5.7), with γ=1 and γ=10. Estimation window is equal to 150 trading days.

Reference Portfolio	Alternative Portfolio	Bootstrap		
γ=1				
		μ_p=12.5%	μ_p=15.0%	μ_p=17.5%
MHAR-RV	EWMA	-68.7	-19.1	30.2
	MVGARCH	-11.8	49.3	109.4
γ=10				
		μ_p=12.5%	μ_p=15.0%	μ_p=17.5%
MHAR-RV	EWMA	-68.5	-18.6	31.3
	MVGARCH	-11.7	49.2	109.2

3.7.Conclusion

We have characterized the economic gains associated with the use of multivariate realized measures of volatility applied to a comprehensive set of twenty Brazilian stocks between February 2006 and January 2011. The forecasting procedure has been based on Corsi's HAR-RV model applied to a multivariate setting, as proposed by Bauer & Vorkink (2011). Portfolio weights have been computed under a volatility timing strategy while economic value relative to alternative multivariate forecasting methods employed a quadratic utility, as in Fleming et al (2001, 2003).

We find that economic gains associated with realized measures increase are substantial for higher levels of the target return when estimation risk is controlled with ex-post information. Using the unconditional mean as a reference for expected returns, an investor would be willing to pay 30.9 and 109.3 basis points to switch from a portfolio based on EWMA and MVGARCH, respectively, to a portfolio based on (MHARV-RV) forecasts, when subjected to a target level of 17.5% a.y. and no restriction to short selling. Economic gains are also robust to changes in the parameters of the utility of the optimization problem. When estimation risk is significant, however, it tends to offset economic gains of realized volatility. Besides, restricting short selling eliminates the association between target returns and economic gains.

For lower levels of the target return, as we observe higher weights on the risk-free asset, economic gains are decreasing and we cannot attest for its superiority over the competing forecasting methods, EWMA and MVGARCH. It is also important to highlight that estimation risk plays a key role on the estimation procedure. When we depart from the "no estimation risk" case, economic gains associated with bootstrapped expected returns display positive values, but high standard deviation figures.

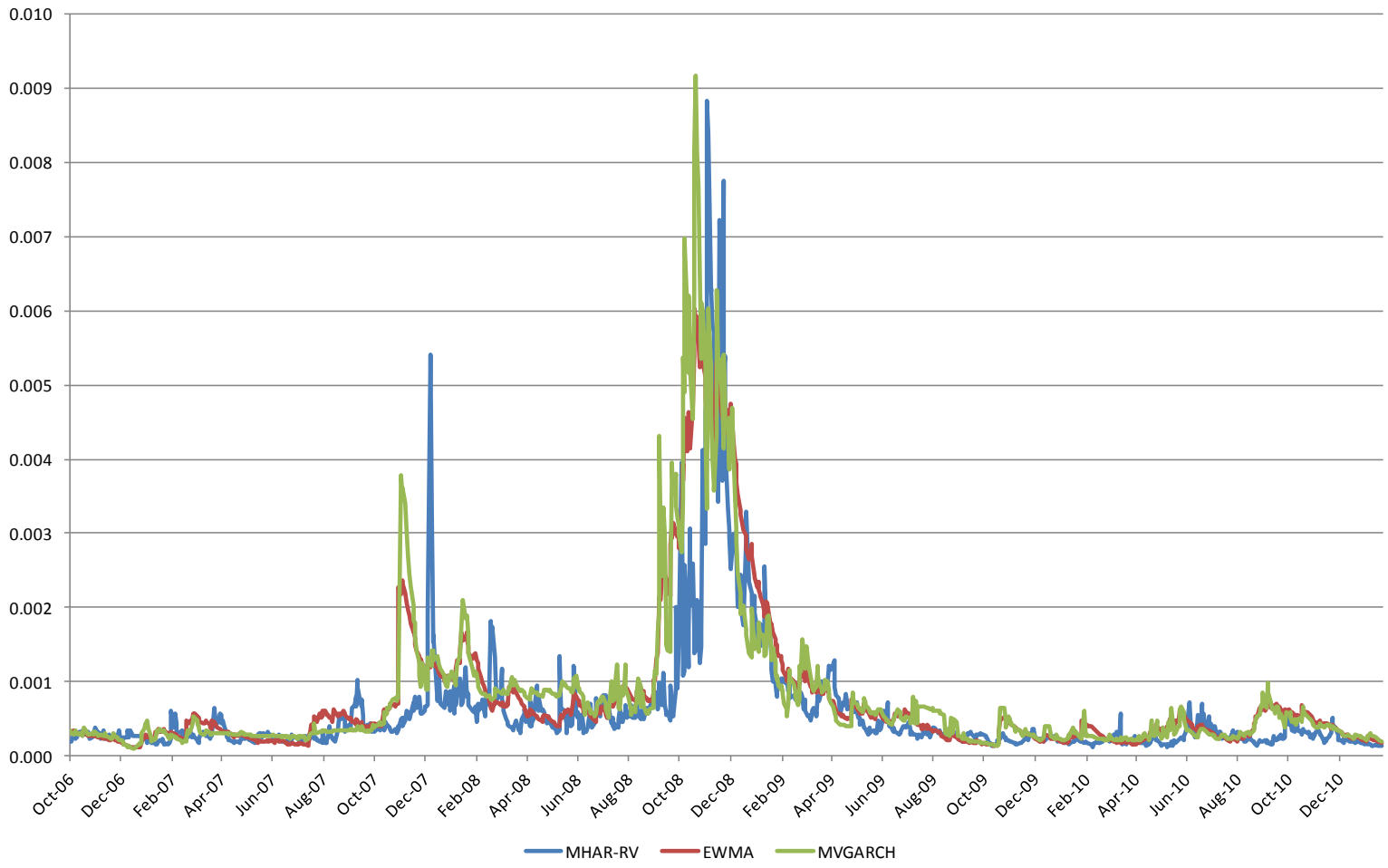
Our results contribute to the literature as we provide evidence of the realized measures' benefits even when are dealing with a great number of assets, all of them with high estimation risk and volatility shifts. Although Fleming et al (2001, 2003) already offered clear indication on such benefits; their work considered a lower number of assets and it is not straightforward to imply that results hold whatever the assets' dimension. We should point out, however, that utility gains are only significant when we control for estimation risk with ex-post information, suggesting that poor forecasts of expected returns offset utility gains associated with realized volatility.

Taylor (2013) investigated the economic value related to volatility forecasts of portfolios based US bond and stock futures. The author notes that the gains associated with the

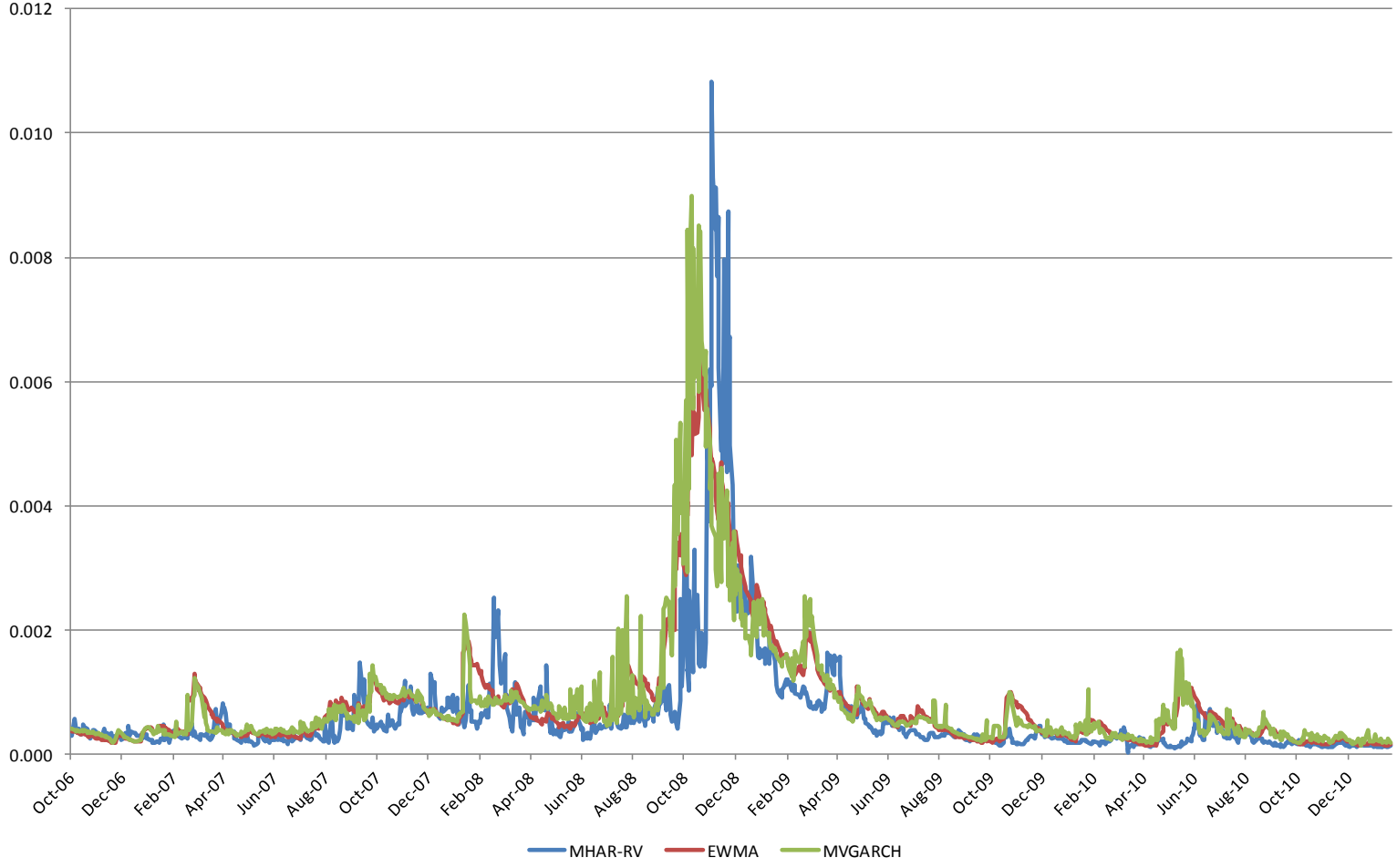
knowledge of volatility dynamics are timely and state-dependent. Hence, future research should consider the use of sub-samples in order to explore dynamic features of the results. Since our choice for the economic utility is arbitrary, another possibility is to assess economic performance by alternative function forms. Finally, proper expected returns' modeling should provide results more independent from estimation risk considerations.

3.8.Annex C

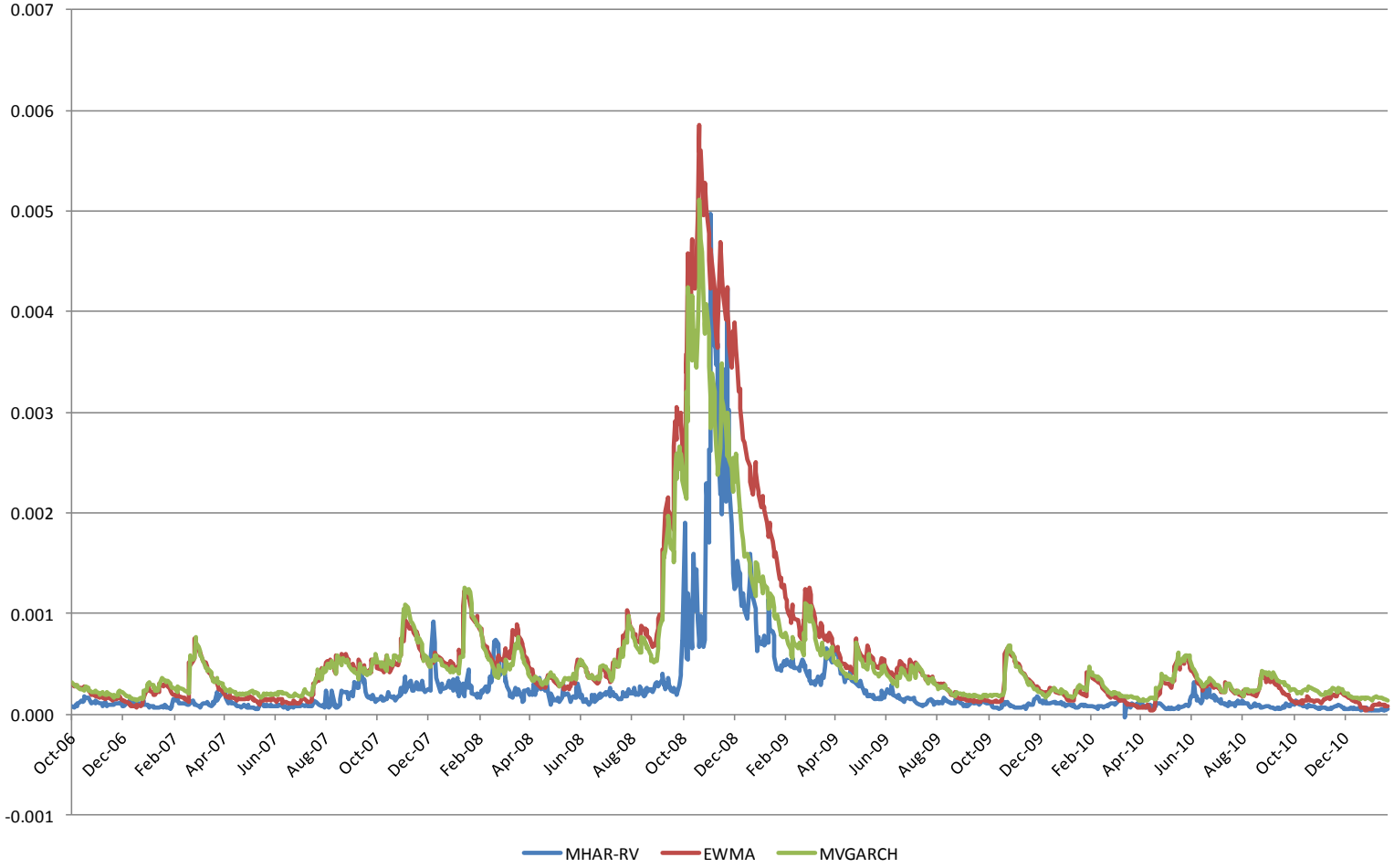
Graph 10: Daily volatility of Petrobras (PETR4) according to different forecasting models (EWMA, MVGARCH and MHAR-RV)



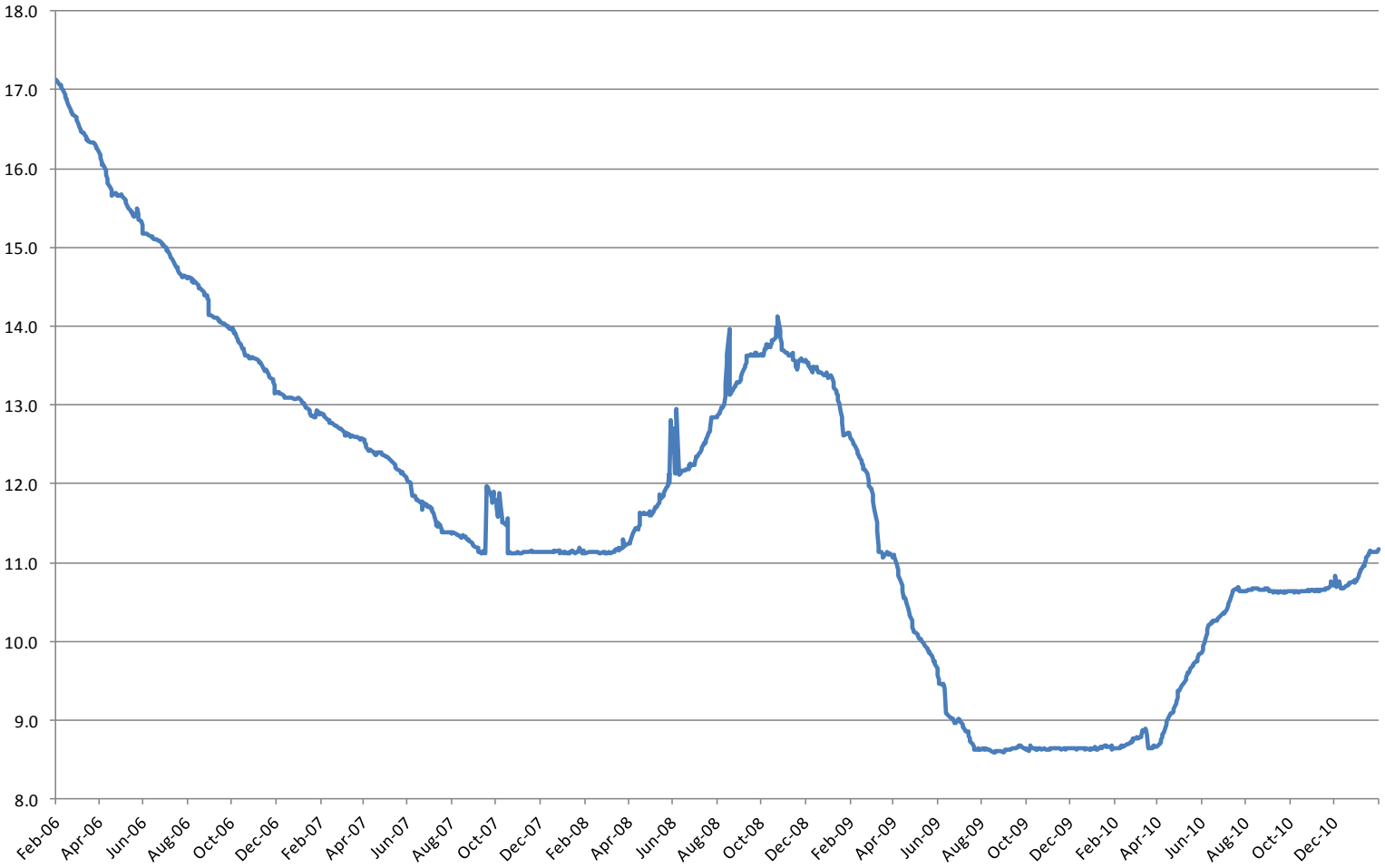
Graph 11: Daily volatility of Vale (VALE5) according to different forecasting models (EWMA, MVGARCH and MHAR-RV)



Graph 12: Daily covariance of Petrobras (PETR4) and Vale (VALE5) according to different forecasting models (EWMA, MVGARCH and MHAR-RV)



Graph 13: Evolution of the risk-free asset between February 2006 and January 2011 (expressed in percent a year)



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