Pontifícia Universidade Católica
do Rio de Janeiro

Luis Eduardo Silbert de Larisch

Evaporating Liquidity in Brazil

Dissertação de Mestrado

Dissertation presented to the Programa de Pós–graduação em Macroeconomia e Finanças of PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor : Prof. Marcelo Cunha Medeiros
Co-advisor: Prof. Pablo Salgado

Rio de Janeiro
February 2021

Pontifícia Universidade Católica
do Rio de Janeiro

Luis Eduardo Silbert de Larisch

Evaporating Liquidity in Brazil

Dissertation presented to the Programa de Pós–graduação em Macroeconomia e Finanças of PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia. Approved by the Examination Committee:

Prof. Marcelo Cunha Medeiros
Advisor
Departamento de Economia – PUC-Rio

Prof. Pablo Salgado
Bahia Asset Management

Prof. Axel Simonsen
Banco Itau Holding Financeira AS

Prof. Carlos Carvalho Viana
Departamento de Economia – PUC-Rio

Rio de Janeiro, February the 17th, 2021

Luis Eduardo Silbert de Larisch

Majored in Economics by Faculdade IBMEC- RJ in 2015(RJ,Brasil)

Bibliographic data

Larisch, Luis Eduardo Silbert de

Evaporating Liquidity in Brazil / Luis Eduardo Silbert de Larisch; advisor: Marcelo Cunha Medeiros; co-advisor: Pablo Salgado. – 2021.

43 f: il. color. ; 30 cm

Dissertação (mestrado) - Pontifícia Universidade Católica do Rio de Janeiro, Departamento de Economia, 2021.

Inclui bibliografia

1. Economics – Teses. 2. Liquidity – Teses. 3. Finanças Quantitativas. 4. Estratégias de Reversão. 5. Reversão de Curto-Prazo. 6. Reversal em Ações. I. Marcelo, Medeiros. II. Salgado, Pablo. III. Pontifícia Universidade Católica do Rio de Janeiro. Departamento de Economia. IV. Título.

CDD: 620.11

To my parents Renata, Luis and Claudio for their support encouragement, and to the one who accompanied and encouraged me closely through these hard years, my love, Taisa Pedrosa.

Acknowledgments

To my advisor Pablo Salgado for the help and partnership while conducting this study.

To PUC-Rio, my professors and to the Economics Department for providing the space and sharing the knowledge used to write this dissertation.

To my parents who provided me with the education and thought me the meaning of love, care, dedication and resilience.

To my uncle for encouraging and sharing the costs of this program.

To Taisa Pedrosa the one who supported and encourage me the most, going through all the tough times of abdication with me.

To my brothers and friends who remained beside me in this period of absence from their lives.

To my colleagues, for helping one another in times of need.

To the professors participating in the Examination Committee.

To all who encouraged me or supported me in any form.

Abstract

Larisch, Luis Eduardo Silbert de; Medeiros, Marcelo Cunha (Advisor); Salgado, Pablo (Co-Advisor). **Evaporating Liquidity in Brazil**. Rio de Janeiro, 2021. 43p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Literature shows that short-term reversal strategies in equity markets can be interpreted as a proxy for liquidity provision. This study examines whether the short-term reversal strategy bears similar results in Brazil, a way less developed and illiquid market. On the developed American stock markets, the expected return of such a strategy appears to be lucrative, strongly time-varying and highly predictable with liquidity and fear indexes such as the VIX index. In the Brazilian, more volatile market, the profitability of such a strategy seem to have reduced in the latest years, and contrary to expectations, the EMBI+ Brazil is the only index with predictive power over such returns while the VIX-EWZ and the Ivol-BR, both proxies to what would be a Brazilian VIX have no predictive power. The expected returns of providing liquidity seem to rise in times of increased risk perception, which indicates that withdrawal of liquidity supply, translated in an increase in the expected returns from liquidity provision, is one of the drivers behind the evaporation of liquidity in times of market turmoil even in developing countries.

Keywords

Quantitative Portfolio; Quantitative Strategies; Short-Term Reversal; Brazil; Stocks Reversal.

Resumo

Larisch, Luis Eduardo Silbert de; Medeiros, Marcelo Cunha; Salgado, Pablo. **Evaporando Liquidez no Brasil**. Rio de Janeiro, 2021. 43p.Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

A literatura tradicional mostra que em mercado desenvolvidos estratégias de reversão de curto prazo no mercado de ações podem ser interpretadas como proxies para provisão de liquidez. Essa dissertação valida esse achado para o cenário brasileiro, um mercado menos líquido e desenvolvido. No mercado americano de ações, o retorno esperado de tais estratégias parece ser lucrativo, variante com o tempo e fortemente previsível usando índices de liquidez e medo tal como o VIX. No Brasil, um mercado mais volátil, a lucratividade de tais estratégias parece ter reduzido nos últimos anos e contrário as expectativas, o EMBI+ Brazil é o único índice com poder preditivo sobre os retornos desta estratégia, enquanto o VIX-EWZ e o Ivol-BR, ambos proxies ao que seria um VIX brasileiro não possuem tal poder. O retorno esperado desta estratégia aumenta em momentos de maior percepção de risco, o que indica que a redução na oferta de liquidez, traduzida em um aumento nos retornos esperados pela provisão por liquidez é um dos motivos para evaporação de liquidez em tempos de grandes agitações até mesmo no mercado brasileiro.

Palavras-chave

Finanças Quantitativas; Estratégias de Reversão; Reversão de Curto-Prazo; Reversal em Ações.

Table of contents

List of figures

List of tables

1
Introduction

In times of financial turmoil, liquidity often becomes scarce. In the most acute instances, liquidity may even evaporate, leading to a complete halt in trades.

The academic literature on the subject suggests that there are at least two reasons for evaporating liquidity. One is that crises amplify asymmetric information problems (Gorton and Metrick (2010)[1]). According to this view, a reduction in liquidity is a symptom of aggravated adverse selection problems. An alternative theory is that market turmoil causes a strain in the inventory-absorption capacity of the market-making sector, either because of a surge in liquidity demand from the public or because the agents that act as market makers reduce liquidity supply in response to elevated risk perception, risk policies, tighter funding constraints or other factors. This dissertation studies the second alternative.

Differently from developed countries, where such situations are less frequent, developing countries may face a situation of evaporating liquidity more frequently, as is the case with Brazil. In Brazil, some of the reasons for such situations include political conflicts, economic instabilities, institutional changes and the contamination of global crises. The more frequent presence of such events makes this market way more volatile and peaks in illiquidity to appear more often.

In the Brazilian stock market, many assets have limited liquidity, and the Brazilian Stock Exchange (B3) Market Maker program only encompasses a reduced amount of stocks. With this in mind, it is important to highlight the role of other investors as liquidity providers which, in the sense of Grossman and Miller(1988)[2], are the agents that accommodate order flow from liquidity motivated traders, buying (selling) when there is an exogenous selling (buying) pressure from a liquidity-motivated noise trader. In this sense, liquidity provision is compensated with a higher expected return, which may be captured by quantitative investors (Hendershott, Jones, and Menkveld (2011)[3]), hedge funds, or even individual investors (Kaniel, Saar, and Titman (2008)[4]) who unofficially perform the role of liquidity providers.

To capture the returns earned by liquidity providers Nagel (2012)[5] creates a theoretical model showing that short-term reversal strategy returns closely tracks the returns earned by providing liquidity. In his model, reversal strategies use lagged returns as a noisy proxy for unobserved market makers inventory imbalances and they profit from the transitory price impact of order flow and the negative serial correlation in price changes that arise from market makers' aversion to absorbing inventory. Adapting the theoretical model to empirical use, by using CRSP data he also finds that the returns of short-term reversal strategies are highly predictable with the VIX index and other proxies for liquidity supply factors. The result obtained are consistent under many different specifications and when decomposing the VIX into conditional volatility and volatility premium with both components predicting reversal strategy return.

Following Nagel(2012)[5], in an attempt to replicate returns similar to providing liquidity, this study uses the short-term reversal strategy of buying stocks that went down and selling those that went up during the previous days, as in Lehman (1990)[6] and Lo and Mackinlay (1990)[7]. This pattern aims to replicate through the variation in returns, the behavior of liquidity providers, that usually sell when the rest of the market buys and buys when the market sells (which tend to coincide with return fluctuations).

This study's focus is to analyze the results of short-term reversal strategies in the Brazilian stock market and examine whether the predictable time-variations observed using CRSP data is also present in Brazil. In the absence of a Brazilian stock market VIX index, I select three proxies that may seem useful for predicting returns and find that only the EMBI+ Brazil has predictive power over the returns in short-term reversal strategies.

Figures 1.1 and 1.2 reflect some of the key findings in this paper. The solid red line plots a three-month moving average of the daily returns from a reversal strategy that invest R$1,00 of capital each day and weights stocks based on the prior five days' return.

The red line in Figures 1.1 and 1.2 show that the reversal strategy returns seem to increase in times of known market turmoil. In 2001, when Brazil was contaminated by the crisis in Argentina, going through a period of energy rationing and with the terrorist attack of 2001, the daily average returns reached an average of 0,40%, falling shortly after. In 2002 with the possible risk of sovereign default given by the possible entry of the new president Luis Inácio, the returns rose again reaching a daily average of 0,28%. The returns also increased in the 2008 subprime crisis, during the election of Dilma Rousseff, and other know events of market turmoil.

While Figure 1.1 rarely displays negative returns, in Figure 1.2 it is noticeable that they are more frequent, which may lead us to question the lower profitability of the strategy in the latest years. Still, even with negative returns, returns increase in times of market turmoil.

As the blue line in the figures shows, this time-variation in the reversal strategy return is remarkably highly correlated with the EMBI+Brazil from 2000 to 2010, while from 2010 to 2020, the correlation does not seem to be as high as in the previous years, possibly due to higher volatility of risk perception. Predictive regressions confirm that the correlation between changes in EMBI+ and reversal strategy returns is predictive, i.e., EMBI+ changes forecast reversal strategy returns on a daily and monthly basis. Both transaction-price and quote-midpoint returns of reversal strategies return similar results. These results lead us to think that EMBI+ proxies for one or more underlying state variables that drive the willingness of market makers to provide liquidity and the public's demand for liquidity.

The results above contribute to literary evidence that reversal strategies are profitable. Data shows that the annualized sharp ratio for transaction price reversal returns is close to 0,93%. This return does not seem to be a premium for tail risk as skewness borders zero under different data treatments.

This dissertation is motivated by the earlier works of Pastor and Stambaugh (2003)[8] that using a short term reversal strategy develop a market-wide liquidity measure pointing to the importance of market-wide liquidity and sensitivity to such factor in asset pricing and Hameed, Kang, and Viswanathan (2010)[9] that find the possibility of predicting returns on short term reversal strategies using large market declines. Previous studies also show that in times of market turmoil financial intermediaries reduce risk appetite (Adrian and Shin(2010)[10]), hedge funds lose asset under management and reduce leverage (Gorovyy, and van Inwegen (2011)[11]) therefore it seems reasonable for such agents to demand higher returns for providing liquidity in times of high risk perception.

Figure 1.1: 3-month moving averages of daily return-reversal strategy returns and the EMBI average fluctuations. (2000-2009)

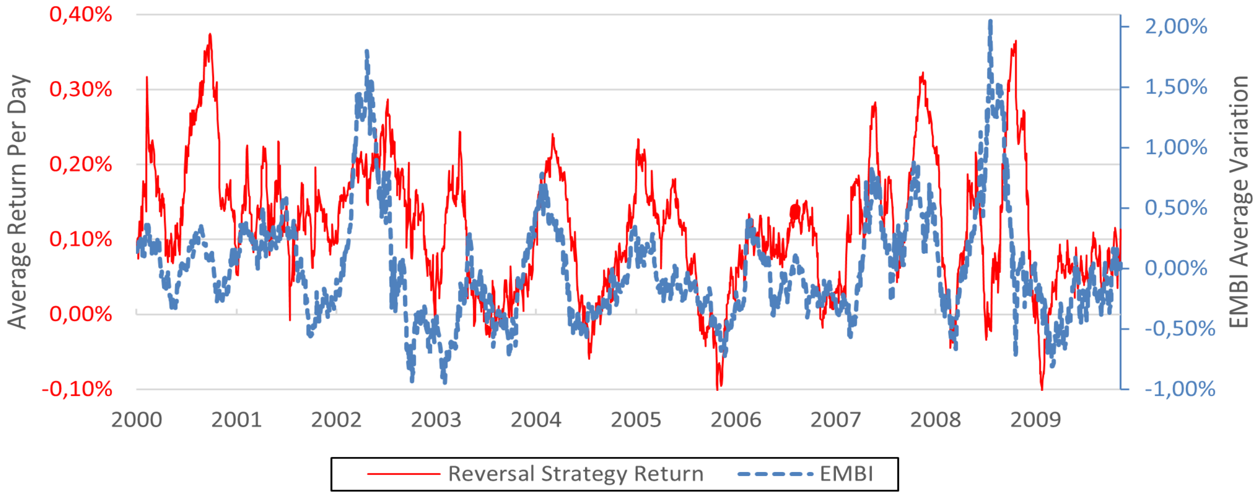

Figure 1.2: 3-month moving averages of daily return-reversal strategy returns and the EMBI average fluctuations. (2010-2019)

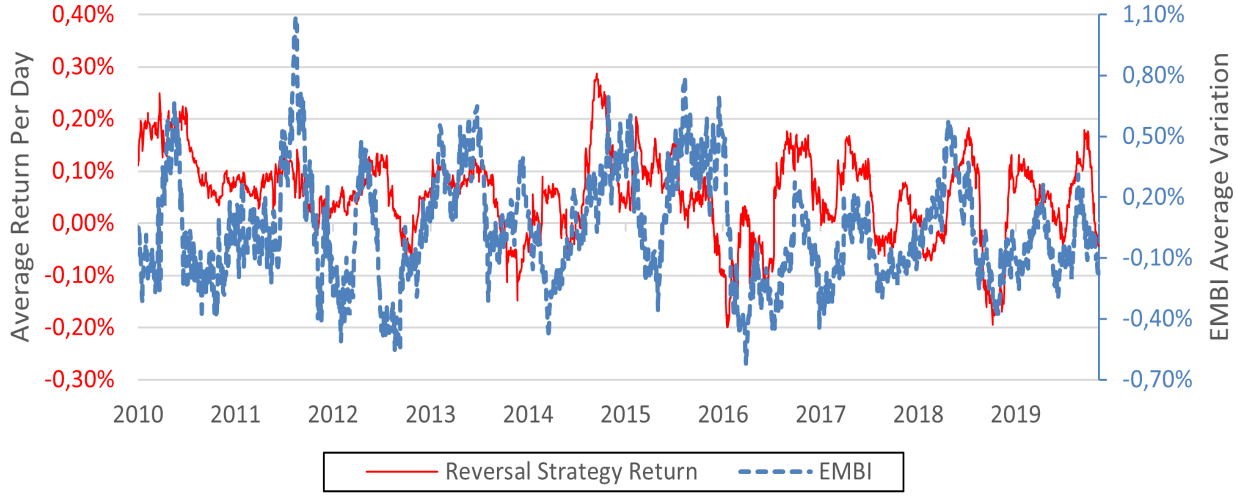

Figure 1.1 and 1.2: 3-month moving averages of daily return-reversal strategy returns and the EMBI average fluctuations. Each day t, the reversal strategy returns are calculated as the average of returns from five reversal strategies that weight stocks proportional to the negative of market-adjusted returns on days t - 1, t - 2, ..., t - 5, with weights scaled to add up to R$1 short and R$1 long.

2
Measuring Returns from Liquidity Provision

2.1
Model

To empirically measure the returns from providing liquidity, it would be necessary to know the inventory positions of the market-making sector, which in the sense of Grossman and Miller(1988)[2], are the agents that accommodate order flow from liquidity motivated traders and are compensated with a higher expected return (by buying at a low price or selling at a high one).

Existing works on the NYSE (Comerton-Forde, Hendershott, Hones, Moulton and Seasholes(2010)[12]) that use proprietary market makers data show that market markers obtain higher expected returns from absorbing order imbalances above compensation for adverse selection. Even though this kind of study ignores the important activities of other agents as liquidity providers, for markets with a significant amount of market makers, this kind of study may be a good proxy for the inventory position of the agents responsible for providing liquidity.

In Brazil, the amount of PN, ON and UNIT stocks under the official market making policy amount to a total of approximately 60 stocks out of 320 such stocks available at the end of 2019. This reduced number of stocks under such policy possibly indicates a higher importance of non-official market makers in the Brazilian market, which suggests that using only official market makers data would not necessarily reflect the returns on providing liquidity.

As a solution for this problem, Nagel(2012)[1] proposes a model that shows that trading strategies that condition on past returns can be used as a noisy proxy to the return from liquidity provision earner by the market-making sector. This strategy may also be used by non-official market makers to capture some of the returns from providing liquidity, either using quantitative strategies or in a way when trading based only on price variation overaction.

He proposes a model with a market composed of three agents, where the value of a stock depends on public information, which has a common factor (f_t) for all stocks, and non-public information. The first agent, the liquidity

[1]For an in-depth analysis on this model see Nagel (2012)

trader, has exogenous demand, the second agent, the informed trader, has his demand based on the impact of the non-public information on the prices, his risk taking capacity and risk perception, and the third agent the market makers' demand depends on his aggressiveness to supply liquidity, price and inventory imbalances and, his best estimate to the nonpublic information.

Following Lehman (1990)[6], he considers a trading strategy with portfolio weight for stock i at the beginning of period t:

$$w_{it}^{R} = -\left(\frac{1}{2}\sum_{i=1}^{N}|R_{it-1} - R_{mt-1}|\right)^{-1}(R_{it-1} - R_{mt-1})\,(1) \qquad (2\text{-}1)$$

Where $R_{mt} \cong \frac{1}{N}\sum_{i=1}^{N} R_{it-1}$ is the equally weighted market index. The strategy earns positives returns if t-1 returns partly reverse in period t. The scaling by the first term $\left(\frac{1}{2}\sum_{i=1}^{N}|R_{it-1} - R_{mt-1}|\right)^{-1}$ guarantees that the strategy is always R$1 short and R$1 long. With a 50% margin on long and short positions, this requires R$1 of capital. The expected return of a portfolio of N stocks is:

$$L_{t}^{R} = -\left(\frac{1}{2}\sum_{i=1}^{N}|R_{it-1} - R_{mt-1}|\right)^{-1}\sum_{i=1}^{N}(R_{it-1} - R_{mt-1})\,R_{it} \qquad (2\text{-}2)$$

The equation (2-2) can be interpreted as the portfolio return of each real invested.

In a scenario with such agents, he shows that in a large cross-section of securities, the realized time-t return from the strategy in (2) is

$$\lim_{N\to\infty} L_{t}^{R} = \rho\sqrt{2\pi}\left(\frac{1}{\gamma}\right)\sigma_{x} \qquad (2\text{-}3)$$

where (i) ρ is the volatility of the unexpected return driven by order flow divided by the total cross-sectional standard deviation of returns (see equation 4), (ii) γ, captures the aggressiveness with which market makers supply liquidity, which is increasing in the risk-bearing capacity of the market making sector, and decreasing in the level of risk and (iii) σ_x is the volatility of unexpected order flow. The returns from supplying liquidity earned by market makers are decreasing in market makers' aggressiveness and increasing in the volatility of unexpected order flow, which can be respectively thought of as the liquidity offer and demand for liquidity.

The presence of ρ originates from the fact that past returns are a noisy proxy for market makers' inventory positions $-x_{it-1}$ because the public information component in returns adds noise unrelated to inventory imbalances. As a consequence, this reversal strategy effectively uses up more capital than the market makers' strategy, because it takes positions proportional to $-(R_{it-1} - R_{mt-1})$, which captures other factors rather than proportional to only the component of $-(R_{it-1} - R_{mt-1})$ driven by x_{it-1} .

From the model, one of the main concerns is that a high value of L_t^R may be a result of fluctuations in ρ , and not in demand for liquidity, or aggressiveness in liquidity provision. In this model

$$\rho \equiv \frac{\left(\frac{1}{\gamma} + \phi\right) \ \sigma_x}{\sigma_R} \tag{2-4}$$

where σ_R represents the total cross-sectional standard deviation of returns, and ϕ reflects the informativeness of non-public information the market makers can capture using the demand of the other agents in the market for whom the market maker will have to provide liquidity.

In this case ρ can rise due to: (a) low variance of public information shocks $(\sigma_{\epsilon\_public})$ (which lowers the denominator σ_R but does not affect the numerator) ; (b) high ϕ (which raises ρ towards one)

For (a), it does not seem reasonable for the variance in public information to lower in times of market turmoil as for (b), the findings in Hendershott and Menkveld (2010)[13], Hasbrouck (1991)[14], and Nagel(2012)[5] suggest that the profits of this reversal strategy should be relatively insensitive, or even inversely related to changes in ϕ.

2.2 Empirical Implementation

To empirically teste the implementation of reversal strategies, this study first uses the data on the Brazilian stock markets obtained from the Brazilian exchange B3 and from Bloomberg from 2000 to 2019.

The appendices A and B present information regarding the specificities of Brazilian data. Appendix A presents the data sources for each series, briefly explains the main difficulty of working with Brazilian stocks market data, its impact in the studied model, and reports the data treatment used in the main part of this article. Appendix B explains the data treatments used in the main section of this article and other alternative treatments, explaining the logic behind the use of each of them.

To define data frequency usage for the model, this study uses as references the earlier works of Hansch, Naik, and Viswanathan (1998)[15] and Hendershott and Menkveld (2010)[13]. Hansch, Naik, and Viswanathan (1998[15]) report that the average half-life of dealer inventory positions on the London Stock Exchange is roughly two days. Hendershott and Menkveld (2010)[13], using NYSE data, find half-lives ranging from half a day to three days therefore using daily frequency may seem to be a reasonable choice to capture imperfect liquidity provision.

Wang (1994)[16] and Llorente, Michaely, Saar, and Wang (2002)[17] find that long-lived private information can induce positive serial correlation at short horizons. This suggests that conditioning reversal strategy on the previous day return may understate the returns from supplying liquidity. To treat for this possibility for each return on t this study will calculate five portfolios with each of them conditioning the asset weights based on the returns of one of the five previous days and average the returns of such portfolios. This approach should also help in the case of short-run continuation and delayed reversal.

Regarding the execution price of the liquidity providers, it is reasonable to think that due to the nature of their trade that they do not pay the bid-ask spread, and instead may even earn returns from the non-adverse selection component of this spread, therefore the use of the closing transaction price seems to be a conservative estimate of their return. However, it would be interesting to see how much is earned from the bid-ask bounce in the transaction process, and how much is attributable to negative serial correlation in quote-midpoint changes, which is why this dissertation will also be including the returns on the portfolio using the midpoint of the bid and ask closing quotes.

As is the case with many other reversal strategies, the one strategy in (2) may present time-varying exposure to different market factors. For example, since the reversal strategy in this paper uses market return as a mean to capture the liquidity providers' inventory, when the market rises, stocks with a low beta will tend to perform below the market return, and stocks with high beta tend to outperform the index, generating a short low beta/long high beta portfolio with a positive conditional beta.

It seems reasonable to hedge for such factors in an attempt to isolate the return obtained from providing liquidity captured by market makers, which may also be hedging for such risk factors, as the factor loadings are straightforward to predict based on the sign of lagged factor realizations. This study will focus on the hedged reversal strategies after eliminating exposure to such factor by first estimating

$$L_t^R = \beta_0 + \beta_1 f_t + \beta_2 (f_t \times sng(f_(t-1))) + \epsilon_t \quad (2\text{-}5)$$

where f_t is the return on the B3 value weighted index and L_t^R is the reversal strategy return. The time-varying beta is $\beta_{t-1} = \beta_1 + \beta_2 sgn\ (f_{t-1})$, which will then be used to calculate hedged returns as $L_t^R - \beta_{t-1} f_t$. The used model does not differentiate between stock in regards of size, liquidity or any other known factors.

3
Time Variation in Expected Return from Liquidity Provision

Table 3.1 reports the summary statistics of the reversal strategy returns. Panel A shows raw return strategies statistics, while Panel B shows similar statistics for hedged returns, which are obtained by eliminating conditional market factor exposure.

Comparing panels A and B for transaction and quote Mid-Points prices, it is possible to see that, as intended, the beta exposure drops from 0.05 to almost zero. There does not seem to be significant differences from both strategies, other than a subtle drop in return, standard deviation, Sharpe ratio, skewness, and a slight increase in kurtosis. This characteristic may be a consequence of the fact that the raw returns portfolio presents a low beta to common market factors. The returns found on Panel B will be the focus of the following analysis.

As shown in Table 3.1 column (1), the strategy earns consistent positive returns while having relatively low daily volatility. The value-weighted index bears a slightly higher daily mean returns of 0,10% but has a standard deviation of 1,54% while the portfolio reaches almost the same return with a standard deviation of 0,62%. The Sharpe Ratio reflects such results, with the index presenting a Sharpe of 0,45, while our strategy has a Sharpe of 0.93 in the same period. In this case, the volatility in returns is not likely the main impediment that deters investors from providing liquidity.

Asymmetric downside risk also does not appear to be a potential explanation for the high Sharpe Ratios. Reversal strategy returns have almost no skewness (or positive depending on data treatment as is the case with some strategies recorded in appendix C), and while there are instances of losses of several percent on a given day, the worst loss in the three-month period for the transaction price strategy is -11,11% comparing to -42,54% of the value-weighted index.

Quote-mid points results are reported on Column (2) and behave in a similar way to column (1), presenting a slight increase in returns along with an increase in skewness.

While the presented returns are attractive, fixed costs for high-speed market access and technological requirements for the successful placement of orders that capture order flow probably plays an important role in preventing more aggressive entry into the liquidity provision business. After accounting for these fixed costs, Sharpe Ratios may become unattractive.

The results present in this section remain constant with other specifications of data treatment as is shown in Appendix C, section C.1.

Table 3.1: Summary Statistics of Reversal Strategy Returns

The daily reversal strategy return is calculated as the average of the returns, on day t, of five sub strategies that weight stocks proportional to the negative of market-adjusted returns on days t-1, t-2, ..., t-5, with weights scaled to add up to$1 short and $1 long. Transaction-price returns are calculated from daily B3 closing prices. Quote-midpoint returns are obtained directly from Bloomberg and are calculated from the mid-points between bid-ask.

	Panel A : Raw returns	
	(1)	(2)
	Transaction. Prices	Quote Mid-Points
Mean return (% per day)	0,09%	0,09%
Median return (% per day)	0,08%	0,08%
Std.dev. (% per day)	0,62%	0,64%
Skewness	-0,12	-0,25
Kurtosis	12,75	14,28
Worst day return (%)	-6,93%	-7,09%
Worst 3-month return (%)	-11,11%	-15,85%
Beta	0,05	0,05
Annualized Sharpe Ratio	1,09	1,12
	Panel B : Returns hedged for conditional market factor exposure	
	Transaction. Prices	Quote Mid-Points
Mean return (% per day)	0,08%	0,09%
Median return (% per day)	0,08%	0,08%
Std.dev. (% per day)	0,61%	0,63%
Skewness	-0,23	-0,37
Kurtosis	12,70	14,53
Worst day return (%)	-6,93%	-7,09%
Worst 3-month return (%)	-11,78%	-17,04%
Beta	0,00	0,00
Annualized Sharpe Ratio	0,93	0,98

3.1 Predicting Returns from Liquidity Provision with VIX

Turning to time-variation in the expected returns from liquidity provision, in the absence of a Brazilian VIX index, I select three indexes that may seem useful to predicting returns and analyze such indexes as predictors to our portfolio returns. This dissertation will only carry forward analyzing the decomposition of the indexes that seem promising regarding its predictive capabilities.

The first index to be analyzed is the EMBI + Brazil, created by JPMorgan, is the only index that has data available since 2000 and reflects the daily basepoints difference in return of a specific portfolio composed of sovereign bonds of a country compared to the daily returns of an American sovereign bonds portfolio. This index is the most used in the Brazilian press and is used to indicate the financial market confidence in the Brazilian economy.

Other than being available since the beginning of our portfolio, there can be found issues with its use. Although this index seems to be appropriate for measuring risk, since its composition is based exclusively on the interest rate spread between countries, it might not only capture risk perception and it may also include other factors related solely to the bonds market, or it can also reflect a change in risk perception exclusive to the USA. This article works with the percentual changes in the EMBI+ Brazil as a predictor of the portfolio returns since this measure more efficiently captures increases and decreases in risk perception, which might lead to an imperfect provision in liquidity.

I will also analyze the EWX VIX Index, created by the CBOE. This index starts along the EWX, in 2008, and uses the same methodology of the S&P VIX applied to the EWX, capturing risk perception through the implied volatility of the EWX options.

Other than starting eight years later than our portfolio, reducing our sample, the main issue with this index is regarding the composition of the EWX, which reflects the Brazilian stocks market in dollars. This may prove to be a problem because this index reflects the risk of a foreign non-hedged investor in the Brazilian stock market. Therefore the EWX VIX reflects not only the risk perception of the Brazilian economy and stock markets but also the risk perception in the exchange rate between both countries, making it lose its relations to our portfolio that is based on the domestic currency.

The final index that will be used is the IVol-BR, developed by FEA-USP. It uses a similar methodology used to compose the S&P VIX based on the implied volatility of IBOV options to measure risk. It differs from the VIX in that it adapts the methodology used to compose the VIX to the way lower liquidity of the IBOV options and specific characteristics of the Brazilian stock market. The only issue with this index is that it only starts at 2011, significantly reducing our sample period.

The regression used to verify the predictive power of the index is:

$$L_t^R = \alpha + \beta * INDEX_{t-5} + R^M + e_t \tag{3-1}$$

Where L_t^R is the hedged closing price portfolio, $INDEX_{t-5}$ is the five

Table 3.2: Pred Risk Perception Indexes

In the daily regressions, the dependent variable is the reversal strategy return on day t (in percent), and the predictor variables are measured at the end of day t - 5. In the monthly regressions, the dependent variable is the monthly average of daily reversal strategy returns, and the predictor variables are measured five days before the end of the month preceding the return measurement month. VX EWZ and IVOL-Br are normalized to a daily volatility measure by dividing it by $\sqrt{2}50$. The variable used in the EMBI+ Brazil are the percentual changes of the index. The control variable RM is the lagged four-week return on the value-weighted of the chosen B3 stocks. Standard errors are reported in parentheses. Quote-midpoint returns are obtained from Bloomberg and calculated from bid-ask midpoints of the of daily B3 closing quotes.

	Panel A : Transaction. Prices					
	Daily			Monthly		
	EMBI+ Brazil	Quote VIX EWZ	Ivol-BR	EMBI+ Brazil	Quote VIX EWZ	Ivol-BR
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0,0008	0,0003	-0,0007	0,0079	0,0008	0,0016
	(0,0001)	(0,0005)	(0,0007)	(0,0001)	(0,0005)	(0,0008)
Index t-5	0,009	0,00006	0,0008	0,013	-0,00019	-0,0008
	(0,003)	(0,0002)	(0,0005)	(0,004)	(0,0003)	(0,0006)
Adj. R2	0,002	-0,0004	0,0009	0,046	-0,0043	0,0129
Intercept	0,0009	0,0005	-0,0005	0,0008	0,0008	0,0016
	(0,0001)	(0,00051)	(0,0007)	(0,0001)	(0,00055)	(0,0008)
Index t-5	0,007	0,00002	0,0007	0,012	-0,00014	-0,0008
	(0,003)	(0,0002)	(0,0005)	(0,003)	(0,0003)	(0,0006)
RM	-0,0054	-0,004	-0,0002	-0,0045	-0,003	-0,0020
	(0,0015)	(0,0024)	(0,0026)	(0,0014)	(0,0026)	(0,0029)
Adj. R2	0,0041	0,00043	0,0007	0,0809	-0,00132	0,0071
	Panel B : Quote Mid-Points					
	Daily			Monthly		
	EMBI+ Brazil	Quote VIX EWZ	Ivol-BR	EMBI+ Brazil	Quote VIX EWZ	Ivol-BR
Intercept	0,0009	0,0011	-0,0004	0,0008	0,0014	0,0016
	(0,0001)	(0,0005)	(0,0007)	(0,0001)	(0,0006)	(0,0009)
Index(m-1) t-5	0,010	0,000	0,000	0,014	-0,001	-0,001
	(0,003)	(0,000)	(0,000)	(0,004)	(0,000)	(0,001)
Adj. R2	0,002	0,001	0,000	0,041	0,039	0,019
Intercept	0,0010	0,0013	-0,0002	0,0009	0,0013	0,0015
	(0,0001)	(0,0005)	(0,0007)	(0,0001)	(0,0006)	(0,0009)
Index(m-1) t-5	0,007	-0,001	0,000	0,014	-0,001	-0,001
	(0,003)	(0,000)	(0,000)	(0,004)	(0,000)	(0,001)
RM	-0,0064	-0,0066	-0,0033	-0,0054	-0,0044	-0,0032
	(0,0016)	(0,0026)	(0,0027)	(0,0017)	(0,0027)	(0,0031)
Adj. R2	0,0046	0,0037	0,0001	0,0793	0,0532	0,0190

day lag of our index measure since our portfolio is constructed with the last 5 days of returns. This study also includes the lagged four-week return on the value-weighted index up until the end of day t - 5 to capture the dependence of reversal strategy profits on lagged market returns documented in Hameed, Kang, and Viswanathan (2010).

Table 3.2 Panel A shows that reversal strategies for transaction prices present mixed results regarding its predictability with the risk perception indexes. Whether in daily or monthly regressions, the VIX EWX (columns (2) and (5)) and the IVol-BR (columns (3) and (6)) have no significant predictable power, yet the EMBI in columns (1) and (4) presents significant predictable power on the daily and even more so at the monthly basis. The magnitude of the coefficient is significant (0.009) relative to the standard error show in parenthesis (0,003). The significance of the EMBI+ lowers when accounting for the lagged market returns as reported in column (1) but remains significant while the predictability of the other risk perception indexes remains insignificant. In (1), the R2 for the daily regression is 0.002, which, although not a high value, seems to be acceptable for a daily return regression.

The monthly regression results present in column (4) Panel A reflect a slight increase in the significance of the regressor but is accompanied by a significant rise in the value of the Adjusted R2 from 0,002 to 0.08.

Panel B displays the results for Quote Mid-Points regressions and reflects similar results compared to Panel A. The coefficients of EWX and IVol-BR remain statistically insignificant, while EMBI still presents significant coefficients in the daily and monthly regressions. The value of the coefficient of Panel B columns (1) and (4) are also similar between both Panels.

Previous work by Nagel (2012) applied to the USA stock market points to the VIX as a good predictor for the returns on this reversal strategy. He also tests other risk perception predictors and finds that they are also a significant predictor. If such results were consistent across countries, it would be expected for the IVol-BR and the VIX-EWZ to perform better than the EMBI+ Brazil, but our findings go in the opposite direction.

One of the possible explanations for these discrepancies between countries is that the VIX for the American case and EMBI+ Brasil for the Brazilian case proxy for the same underlying state variable while the Ivol-BR and the VIX-EWZ do not serve such purpose. This possibility would be counter-intuitive in that the predictors' composition is not relevant. In this case, it seems reasonable that the returns on providing liquidity are related to the reduction in risk appetite of liquidity providers whose risk-management constraints in the Brazilian case may be more related to the EMBI+ rather than the VIX

Figure 3.1: In-sample predicted reversal strategy returns of transaction prices. (2000-2010)

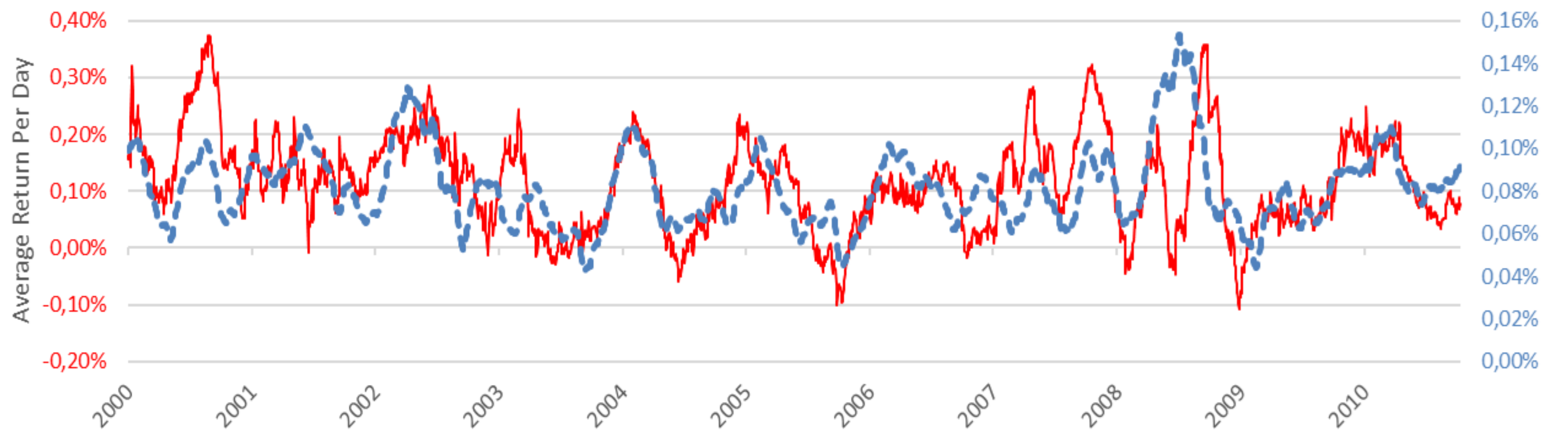

Figure 3.2: In-sample predicted reversal strategy returns of transaction prices. (2011-2019)

Figures 3.1 and 3.2: The figures shows 3-month moving averages of daily reversal strategy returns and of fitted values from predictive regressions on lagged EMBI+ as in columns(1) of table 3.2. The forecasting include the control variable RM, which stand for lagged four-week return on the value-weighted of the chosen B3 stocks.

EWZ and the Ivol-Br, leading to higher returns, this may be explained by the fact that the EMBI+ is the most well know and used risk perception index in Brazil.

Another possible explanation is that the EMBI+ Brazil captures a different state variable that is also a predictor of the reversal returns. Since foreign investor may be one of the relevant liquidity providers, it may be the case that with a rise in the EMBI+, such investor marginally obtains more returns from investing in other investments rather than providing liquidity, reducing the offer on providing liquidity, which would lead to an increase in returns.

Figures (3.1) and (3.2) show the results of in-sample forecasting using the regression with Rm in column (1) for transaction prices. This shows that while the coefficients for the most efficient regression are significant, such an index alone does not seem to generate a good forecasting fit as it only explains a small amount of the daily results.

Figures (3.3) and (3.4) show the results of out-of-sample forecasting. Figure (3.3) shows the out-of-sample fitted values when the predictive regression is estimated with data up to the end of December 2006. Figure (3.4) shows the out-of-sample fitted values when the predictive regression is estimated with data up from 2010 to 2017. As was the case for the in-sample, the out-of-sample plots return similar results for transaction-price returns and still do not explain most of the variation in returns.

Figure 3.3: Out-sample predicted reversal strategy returns of transaction prices. (2000-2010)

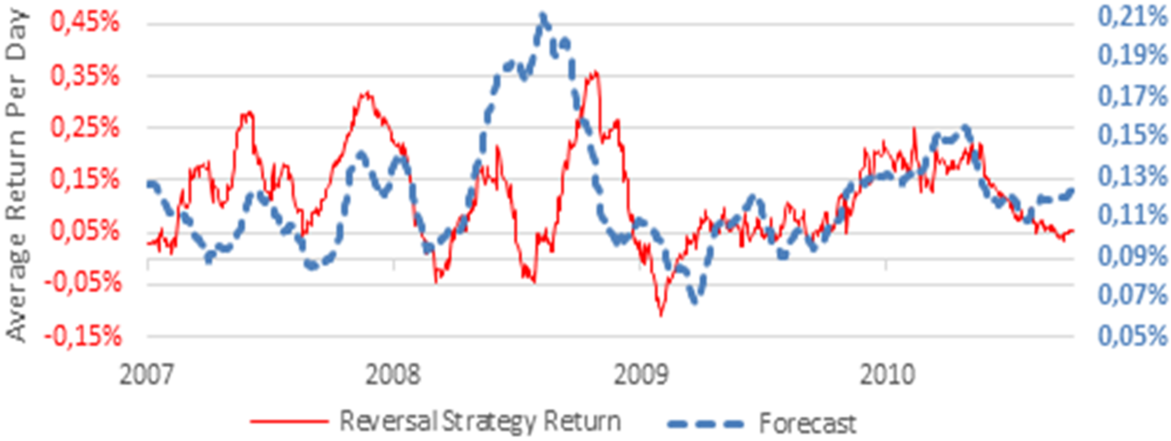

Figure 3.3: Shows 3-month moving averages of daily reversal strategy returns and the out-of-sample fitted values when the predictive regression is estimated with data up to the end of 2006.

Figure 3.4: Out-sample predicted reversal strategy returns of transaction prices. (2010-2019)

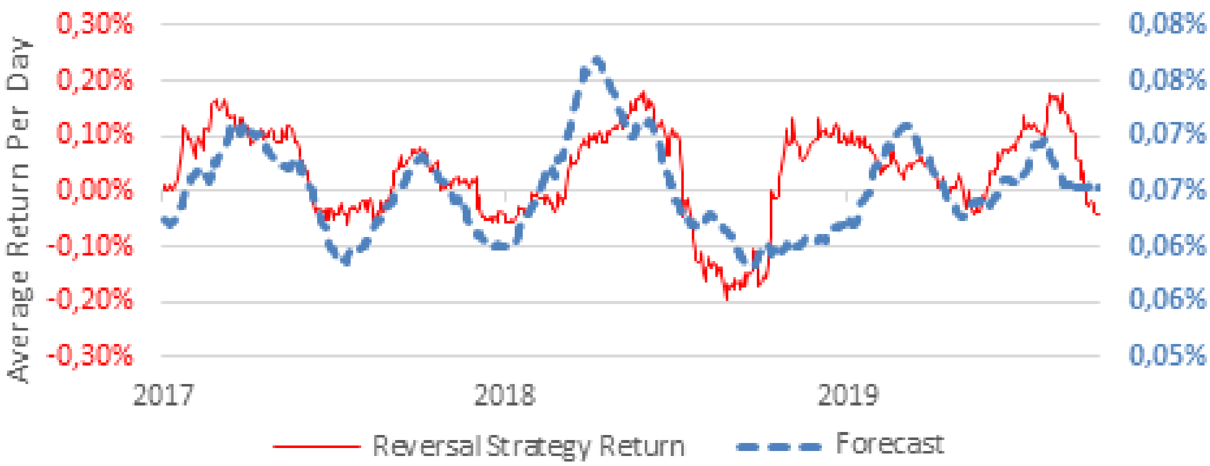

Figure 3.4: Shows 3-month moving averages of daily reversal strategy returns and the out-of-sample fitted values when the predictive regression is estimated with data up from 2010 to the end of 2016.

Overall, the results obtained expose the EMBI+ as good predictor from 2000 to 2010, and a moderate one for the following years.

If implementations costs are one of the impediments for more aggressive entry into the liquidity provision business, then one of the possible explanations to the loss of predictive capability and a significant reduction to return from liquidity provision from 2011 to 2019 might be that some agents might have started to explore this strategy due to the reducing cost of high-frequency trading and of technological implementation in the later years generating a higher offer of liquidity and a lower return for providing liquidity.

The results above raise the question of whether then EMBI+, as an index available for a wide number of markets, would also prove to be a good predictor of reversal strategies in those countries. An extension of this study to other countries may generate interesting results, and if proven true, a portfolio composed of reversals in different countries might provide an even better relation of risk-return.

Appendix C, section C.2 reevaluates the results present in this section with 17 different specifications of data treatment reaching similar results, proving that the results displayed in this section are not only a result of data treatment selection.

4 Conclusions

This dissertation reinforces the idea that short-term reversal strategy returns can be interpreted as proxies for the returns from liquidity provision earned by the market-making sector even when applied to Brazil, a developing country with a more volatile market.

The returns on providing liquidity seem to lower in the recent years, either due to a lower risk perception or due to technological advance and reduction in high frequency trading costs, which decreases the cost of implementation of such strategies, resulting in the presence of more agents applying such a strategy generating a higher offer of liquidity provision.

While the VIX proved to be a good predictor of reversal strategies in the USA, the same did not happen for Brazilian proxies of the VIX. Differently from what was expected, the index with the most predictable capability on the studied reversal strategy was the EMBI+ Brazil, and whether such a result supports Adrian and Shin (2010), who argue that variations in financial intermediaries' risk appetite are driven by risk-management constraints, or whether such results are a consequence of a lowering in stocks liquidity offer by foreign agents due to increases in the sovereign interest spreads is not known and may prove to be a topic of further study.

As shown, in times of financial market turmoil, indicated by positive changes in the EMBI+, the expected returns of these reversal strategies rise predictably and dramatically. Thus, at least part of the reason for the evaporation of market liquidity during periods of financial market turmoil seems to be that liquidity providers demand a higher expected return from liquidity provision.

Differently from the VIX, as the EMBI+ is present in many other countries, further application of such a predictor of other countries may provide fruitful insights to liquidity provision and reversal returns due to it being a worldwide available index.

A
Data Set

From B3 (Brazilian exchange), I obtain non adjusted trade data for all assets, which is a free data set and comes directly from the Sao Paulo exchange. Since the B3 data set is not adjusted for corporate events, such as dividends, splits, and ticker modifications, this study only uses B3 price data and obtains the corporate events price adjusted data from Bloomberg Terminal.

From Bloomberg, we obtain for the stocks the Quote Mid-points Price(adjusted), transaction price (Adjusted and not adjusted), Market Cap, and Volume. We also obtain daily data on the risk-free asset (CDI) and on the VX EWZ. We also obtain the EMBI+Brazil data from IPEA and the Ivol-BR data from NEFIN FEA-USP . [1]

The stocks were selected using the B3 data set, which includes options, futures, and many other derivatives. In this set, we require for the asset to have share code 10(stocks), database code 2 (representing the standard batch), be share types ON, PN, and UNIT, the ticker code must finish with a number (therefore removing the MB shares) and be available at the end period of the sample (2019). After implementing such filters, we are left with 320 stocks. Although there is no clear motive to believe that, in such a sample, picking only survivors could produce other biases that affect our portfolio.

Table A.1 explores the amplitude in price variation of adjusted and non-adjusted transaction prices. This basic analysis only shows us the importance of working with adjusted prices and shows the abnormal amplitude of prices and therefore returns of non-adjusted price series. It is interesting to notice that although lowering the frequency of high amplitude in price, treating for corporate events still leaves us with some unordinary price variation in stocks.

Due to the way the portfolio weights are created in equation (1) (not considering the volume of trade), peaks in return from single assets generate high exposure to single stocks in the following periods. The amplitude analysis above shows us that significant price fluctuations may be present even in the adjusted price series. One of the reasons this happens is related to the infrequent trading of some stocks due to either small price or due to liquidity issues, resulting in low traded volume or absence of trade in some days and huge

[1]http://www.nefin.com.br/principal.html

Table A.1: Price Amplitude

Amplitude is calculated as the maximum minus the minimum price of a stock in the whole data set.

	Price Amplitude	
Amplitude[1]	B3	Bloomberg
(0,40]	53,14%	66,14%
(40,80]	19,81%	19,75%
(80,120]	8,81%	4,39%
(120,160]	3,46%	2,19%
(160,200]	3,14%	0,63%
(200,240]	1,26%	0,63%
(240,280]	0,94%	0,00%
(280,320]	1,26%	0,94%
(320,360]	0,31%	0,31%
(360,400]	0,94%	0,31%
(400,+8]	6,93%	4,71%

[1]Rounded to the dozens

fluctuations on the following ones. These fluctuations produce high volatility to our portfolio's returns, and this study's objective is to capture market-wide returns due to providing liquidity, thus these outliers create a disturbance when attempting to capture the desired premium.

For this study, multiple filters for the price data were prepared with the intention of removing the disturbances present in the data set and to better understand the source of the returns obtained by providing liquidity. Appendix B explains the filters while Appendix C executes the consistency test of the strategy under different data treatments.

In the main section of this article, we remove stocks that i) have a price below 1 at the end of the previous month, ii) excess market returns below or above 30%, and iii) minimum monthly volume above 20.000.

Due to recording errors in the bid and ask prices, the mid-price series presents cases in which the prices vary almost -50% or 100% in a day only to return to the correct price in the following day. As to remove this distortion, I replace mid-price data with closing price data when the difference between the quote mid-points and closing price is smaller or bigger than 10% of the closing price.

B
Data Removal Filters

B.1
Price Filters

By using B3 and BBG data I plan to remove the stocks that have their last monthly price below a specific arbitrary price, decided in this article as R$1, also known as penny stocks . Due to having low prices penny stocks are a source of volatile returns since each tick up or down is equivalent to a 1% positive or negative return. In response to this kind of volatility some would expect penny stocks to have low lower traded volumes. Still, we do not want this kind of treatment to reduce our sample size significantly.

Table B.1: Penny Stocks x Iliquid Stocks

	B3 Data			Bloomberg Data		
Year	% Penny	% Absence	Vol. x Price	% Penny	% Absence	Vol. x Price
	(1)	(2)	(3)	(4)	(5)	(6)
2000	8,29%	72,47%	82,22%	11,65%	61,12%	77,47%
2001	14,51%	70,01%	72,76%	16,99%	60,09%	69,64%
2002	16,15%	66,54%	71,09%	17,27%	58,87%	69,02%
2003	14,80%	63,91%	74,20%	15,97%	57,03%	73,04%
2004	11,97%	61,41%	75,83%	13,04%	53,92%	75,20%
2005	7,66%	57,66%	78,26%	9,08%	49,76%	78,16%
2006	7,12%	54,62%	83,11%	7,96%	45,74%	81,96%
2007	4,93%	45,68%	89,87%	4,38%	34,66%	88,72%
2008	6,52%	41,07%	88,77%	6,44%	29,37%	88,70%
2009	6,59%	39,90%	86,83%	7,42%	28,89%	86,52%
2010	5,39%	35,62%	88,99%	6,38%	25,56%	88,15%
2011	6,43%	34,14%	87,21%	7,38%	23,60%	87,31%
2012	8,01%	32,50%	84,48%	8,91%	23,89%	83,68%
2013	8,74%	31,07%	82,80%	10,45%	23,35%	81,11%
2014	8,70%	28,74%	83,53%	10,46%	21,54%	80,84%
2015	6,29%	25,28%	88,62%	7,30%	17,71%	85,98%
2016	2,37%	19,57%	91,10%	2,77%	12,18%	89,92%
2017	0,79%	12,52%	95,03%	0,94%	6,97%	94,25%
2018	1,23%	7,95%	95,79%	1,18%	4,05%	95,02%
2019	0,49%	4,48%	98,11%	0,48%	1,98%	97,46%
Average	7,35%	40,26%	84,93%	8,32%	32,01%	83,61%

Columns (1) and (4) of table B.1 show that the number of penny stocks removed per year is not very significant, while columns (2) and (5) show that removing such stocks does not significantly influence our sample size. Columns (3) and (6) investigate in each year if the penny stocks removed from our data corresponds with the lowest traded stocks. For example, in 2000, 8,29% of the stocks where penny stocks in a specific month end of the month, so we analyze the 8,29% lowest average monthly volume stocks in that year to see if they overlap with the penny stocks. The result in these columns reflects the similarity (%) in data sets when removing for penny stocks against removing the equivalent lowest volume stocks. Looking at the results, we can conclude that removing penny stocks does not correspond with removing low volume stocks.

B.2
Volume Filters

Since we still must worry about price corrections due to infrequent trading, it seems essential to create a mechanism to avoid high volatility in returns based on price correction due to infrequent trading. Using BBG volume data, we build multiple filters for removing such stocks.

To remove these disturbances, I design three different types of volume filters that are applied on monthly basis and affect the portfolio in the following month. To simplify, if the monthly data of specific stock fulfills the filter requirements, the stock is not considered when determining the portfolio composition in the following month.

To not leave any data out of the filter, in the total absence of volume data in a specific month, we also exclude the data of the following month from the portfolio construction. Although not treated as a filter, removing the data of the first month of a stock is in itself a filter as it removes abnormal returns due to IPOs that, as literature shows, do not present short term reversals.

The first filter type looks for stocks that have the lowest monthly average volume based on a specific decile of the stock, for example, filtering the first decile (10%) of all the stocks with the lowest monthly trade volume and removing the data of the following month. This treatment allows knowing how much data is being removed but does not necessarily remove the disturbance, since in months with low market liquidity, the threshold for removal might be close to zero.

The second filter looks for stocks that have their monthly average volume below a specific value, for example, searching for stocks with monthly average volume below 10.000. This filter does not allow us to select the exact amount of stocks filtered, thus possibly affecting sample size, and it also does not capture corrections in the middle of the month, since in the same month a stock might not be traded for multiple days, and in the correction date, the traded volume might be big enough for the average monthly volume to be above the threshold.

The third filter searches for stocks that have their monthly minimum volume below a specific value, for example, stocks with monthly minimum volume below 1.000. This allows us to capture stocks that have inconstant low liquidity and might have peaks in traded volume in the correction date.

B.3 Excess Return Filter

Another way to remove such disturbances is to directly remove stocks that had an excess return very different from the market return. In the case of a combination of filters, as was done in the main section of this article, this filter uses the remaining data after the previous filters and then calculates a temporary equally weighted market return index used to remove excess return. It is applied to daily data and searches for stocks that performed way above or below the market return. For example, suppose a stock had a return of 40% or -40% in a day where the market return was 1%, by removing excess return above or below 30%, we manage to remove this disturbance

In our strategy, since we decide the weight of our portfolio in equation (1) by looking at excess return, by removing such stocks, we prevent it from having high exposure to a specific stock. Since liquidity providers are also averse to risk, it is reasonable to believe that they might not provide liquidity for stocks that had such variations, or at least that such a stock would not have a significant weight in their inventory.

C
Robustness to Data Treatment

In this section, I evaluate the robustness of this study's findings to data treatment by creating multiple portfolios with different filter specifications and analyzing the results. The following analysis uses transaction prices.

Table C.1 shows 16 portfolios created using different data treatment filters as explained in Appendix B.

Table C.1: Portfolios Treatments

	Portfolios																
Filters	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Price < 1		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1st Volume Decile			x														
Average Volume < 10.000				x													
Average Volume < 25.000					x												
Average Volume < 50.000						x											
Average Volume < 100.000							x										
Min Volume < 1k								x									
Min Volume < 5k									x								
Min Volume < 10k										x							
Min Volume < 20k											x						
Min Volume < 50k												x					
$\lvert$Exceding Return$\rvert$ > 50%													x				
$\lvert$Exceding Return$\rvert$ > 30%														x			
$\lvert$Exceding Return$\rvert$ > 20%															x		
$\lvert$Exceding Return$\rvert$ > 10%																x	
$\lvert$Exceding Return$\rvert$ > 5%																	x

C.1
Descriptive Statistics

Table C.2 shows the descriptive statistics and a creative measure of efficiency in removing disturbances of all 16 portfolios with raw returns on Panel A and with hedged returns on Panel B.

Comparing Panel A with Panel B, the mean returns, standard deviation, skewness, and Sharpe are almost identical with a slight reduction on Panel B, while kurtosis seems to be slightly lower in Panel A. As can also be observed, eliminating conditional market factor exposure on Panel B does not significantly modify either the worst day or 3-month worst return, this indicates that these atypical returns have no relations to market exposure, but to the outlier, as expected. As per the Beta, it reduces from 0.05 to virtually zero as was intended. For this reason we will be comparing the results in Panel (A).

Table C.2: Summary of Descriptive Statistics Under Distincs Data Treatment

The daily reversal strategy return is calculated as the average of the returns, on day t, of five sub-strategies that weight stocks proportional to the negative of market-adjusted returns on days t-1, t-2, ..., t-5, with weights scaled to add up to \$1 short and \$1 long. Transaction-price returns are calculated from daily B3 transaction prices. the sample period runs from January 2000 to December 2019. Each column represents a portfolio constructed by applying different data removal filters as described in Table C.1

	Portfolios																
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Raw Returns																	
Mean return (% per day)	0,48%	0,21%	0,19%	0,10%	0,09%	0,07%	0,07%	0,15%	0,12%	0,10%	0,09%	0,07%	0,17%	0,17%	0,14%	0,11%	0,06%
Median return (% per day)	0,27%	0,16%	0,17%	0,10%	0,08%	0,06%	0,05%	0,15%	0,11%	0,10%	0,09%	0,06%	0,16%	0,15%	0,13%	0,10%	0,05%
Std.dev. (% per day)	2,86%	2,62%	1,21%	0,80%	0,74%	0,70%	0,64%	0,93%	0,82%	0,80%	0,75%	0,70%	0,85%	0,69%	0,61%	0,52%	0,45%
Skewness	16,67	22,73	-9,34	-1,72	-0,82	-1,04	0,10	-2,38	-1,61	-1,72	-0,59	-1,04	-0,68	0,39	0,54	0,75	0,81
Kurtosis	668,48	991,48	310,44	41,81	32,00	27,30	14,43	43,34	33,90	41,81	29,84	27,30	36,13	9,77	10,25	12,59	14,08
Worst day return (%)	-40,16%	-41,14%	-41,49%	-13,26%	-10,79%	-9,85%	-5,90%	-13,93%	-12,16%	-13,26%	-10,38%	-9,85%	-13,67%	-4,76%	-3,69%	-3,11%	-2,91%
Worst 3-month return (%)	-60,82%	-61,62%	-24,18%	-25,76%	-14,28%	-19,37%	-12,59%	-21,44%	-23,00%	-25,76%	-16,81%	-19,37%	-26,61%	-11,78%	-11,76%	-9,67%	-7,95%
Beta	0,05	0,06	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,05	0,06	0,06	0,06	0,06
Annualized Sharpe Ratio	3,85	0,98	2,01	1,09	0,83	0,36	0,50	1,99	1,38	1,09	0,94	0,36	2,65	3,17	2,75	1,93	0,50
Sharpe/|Worst 3-m|	6,33	1,59	8,30	4,23	5,83	1,87	4,01	9,28	5,98	4,23	5,61	1,87	9,96	26,90	23,38	19,96	6,23
Panel B : Returns hedged for conditional market factor exposure																	
Mean return (% per day)	0,48%	0,20%	0,18%	0,10%	0,08%	0,06%	0,06%	0,15%	0,11%	0,10%	0,09%	0,06%	0,17%	0,16%	0,14%	0,10%	0,06%
Media return (% per day)	0,27%	0,15%	0,16%	0,10%	0,08%	0,06%	0,06%	0,14%	0,11%	0,10%	0,08%	0,06%	0,15%	0,15%	0,13%	0,09%	0,05%
Std.dev. (% per day)	2,86%	2,62%	1,20%	0,79%	0,73%	0,69%	0,63%	0,92%	0,81%	0,79%	0,74%	0,69%	0,84%	0,68%	0,60%	0,50%	0,44%
Skewness	16,71	22,80	-9,48	-1,83	-0,89	-1,17	0,00	-2,49	-1,60	-1,83	-0,64	-1,15	-0,75	0,28	0,32	0,46	0,66
Kurtosis	670,32	995,29	315,84	43,75	33,02	28,20	14,19	45,11	35,49	41,50	30,73	28,13	37,38	9,37	8,64	9,48	12,43
Worst day return (%)	-40,15%	-41,15%	-41,49%	-13,39%	-10,79%	-9,84%	-5,88%	-13,94%	-12,30%	-13,39%	-10,34%	-9,84%	-13,62%	-4,76%	-3,68%	-2,63%	-2,91%
Worst 3-month return (%)	-61,26%	-62,01%	-24,68%	-26,17%	-14,57%	-19,49%	-12,73%	-21,72%	-23,13%	-25,86%	-17,05%	-19,43%	-26,86%	-11,98%	-12,06%	-9,95%	-8,17%
Beta	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Annualized Sharpe Ratio	3,76	0,92	1,90	0,96	0,69	0,22	0,37	1,87	1,24	0,96	0,81	0,22	2,50	2,99	2,56	1,75	0,32
Sharpe/|Worst 3-m|	6,14	1,48	7,70	3,68	4,77	1,14	2,88	8,59	5,36	3,71	4,75	1,14	9,33	24,99	21,23	17,63	3,98

Beginning with the price filters applied to portfolio (1), we verify that removing penny stocks lowers our returns significantly but doesn't change our standard deviation significantly. Kurtosis and skewness also increase, which points that while penny stocks generate higher reversal returns, they also possess higher asymmetric downside risk. Removing penny stocks does not decrease the worst day and 3-month returns, which brings us to the conclusion that excluding penny stocks does not correct the disturbances we desire. Our creative measure of efficiency reflects that removing penny stocks reduces returns while not removing specific stock returns despite this, I follow Nagel(2012), and in the following portfolios, always remove penny stocks from our sample, therefore this portfolio will work as the basis for comparison.

Regarding the volume filter, we first analyze the volume lowest decile volume filter present in portfolio (2). In this case, we see together with a slight decrease in return, a significant reduction in standard deviation, and the worst 3-month return, but this procedure still does not manage to capture the disturbance that is leading to the worst day return of 41.49%.

The filters in (3), (4), (5), and (6) search for stocks that had an increasingly average volume below a volume threshold, that starts at (3), with a volume value of 10.000, and reaches 100.000 in portfolio (6). In (3), we notice a significant decrease of daily standard deviation from 2.62% in (1) to 0.80%, an improvement of the worst day return to -13.26%, and 3-month worst returns to -25%, which. The Sharp Ratio remains almost unchanged compared to (1), and our measure of efficiency points to better removal of disturbances with an increase from 1.59 in (1) to 4.23 in (3). The gradual increase of volume threshold from (3) to (6) reduces extreme returns but causes a significant reduction in Sharpe ratio and a decrease in filter efficiency. The drop in returns goes according to our expectation, which relates to the fact that this strategy aims to capture returns on providing liquidity, and the need for liquidity for stocks that have a monthly average volume of 100.000 should be lower than stocks with a monthly average volume of 10.000.

The filters in (7), (8), (9), (10), and (11) search for stocks that had an increasingly minimum monthly volume below a specific value, that starts at (7) with a volume value of 1.000 and reaches 50.000 in portfolio (11). In (7) we observe a slight decrease in median return (0.15% to 0,14% in(1)) and a more significant decrease in mean return (0.20% to 0.15%). The standard deviation, worst daily, and 3-months returns fall significantly, and our measure of efficiency increases from 1.59 to 9.28 while Sharp Ratio rises to 1.87. Following what happened in the previous volume in filters (6) to (11), the gradual increase in the filter reflects a gradual reduction in returns. Due to its

Table C.3: Descriptive Statistics for mixed data treatment portfolios

	Portfolios (17)	(18)	(19)	(20)
Price < 1	x	x	x	x
1st Volume Decile				
Average Volume < 10.000				
Average Volume < 25.000				
Average Volume < 50.000				
Average Volume < 100.000				
Min Volume < 1k	x	x		
Min Volume < 5k				
Min Volume < 10k			x	
Min Volume < 20k				x
Min Volume < 50k				
|Exceding Return| > 50%				
|Exceding Return| > 30%		x	x	x
|Exceding Return| > 20%	x			
|Exceding Return| > 10%				
|Exceding Return| > 5%				
Panel A : Raw returns				
Mean return (% per day)	0,13%	0,15%	0,10%	0,09%
Median return (% per day)	0,12%	0,14%	0,09%	0,08%
Std.dev. (% per day)	0,59%	0,66%	0,62%	0,62%
Skewness	0,29	-0,12	0,04	-0,12
Kurtosis	9,91	11,50	11,72	12,75
Worst day return (%)	-4,05%	-5,83%	-6,47%	-6,93%
Worst 3-month return (%)	-10,54%	-12,12%	-10,23%	-11,11%
Beta	0,05	0,06	0,05	0,05
Annualized Sharpe Ratio	2,50	2,74	1,38	1,09
Sharpe/|Worst 3-m|	23,72	22,62	13,45	9,80
Panel B : Returns hedged for conditional market factor exposure				
Mean return (% per day)	0,13%	0,14%	0,09%	0,08%
Media return (% per day)	0,12%	0,14%	0,09%	0,08%
Std.dev. (% per day)	0,58%	0,65%	0,61%	0,61%
Skewness	0,13	-0,23	-0,05	-0,23
Kurtosis	9,41	11,71	11,87	12,70
Worst day return (%)	-4,04%	-5,83%	-6,46%	-6,93%
Worst 3-month return (%)	-10,54%	-12,12%	-10,23%	-11,78%
Beta	0,00	0,00	0,00	0,00
Annualized Sharpe Ratio	2,33	2,58	1,22	0,93
Sharpe/|Worst 3-m|	22,14	21,26	11,97	7,87

superior efficiency compared to other volume filters, this filter is the one used in the main section of this article.

The filters in (12), (13), (14), (15), and (16) search for stocks that decreasingly had a daily excess return above or below a specific value, that starts at (12) with a value of 50% and reaches 5% in portfolio (16). The filtered stocks are excluded from the portfolio composition on the following day. In (12), when compared to (1) we observe no decrease in median return, a decrease in mean return (0.20% to 0.17%), standard deviation (2.62% to 0.85%), worst daily (-41.14% to -13.67%) and 3-month (-61.62% to -26.61%) returns and an increase in Sharpe(0.98 to 2.65) and efficiency (2.38 to 19). This indicates that this filter appears to be the most efficient in removing outliers as it acts directly on the outliers. Following what happened in the previous volume filters the gradual decrease in excess returns acceptance from (12) to (16) reflects a gradual reduction in returns, worst day returns but different from before efficiency increases and reaches a maximum of 26.90 at (13) before dropping to 6.23 at (16). The efficiency present in this filter leads us to use it in the main section of the article.

For the main part of this article, we select a combination of the filters present in (10) and (13) that while not having the highest efficiency seems to be the middle term between efficiency and returns as described by table C.3 in portfolio (20).

Table C.3 below shows that the results between different filters combination seem to follow the return-efficiency tradeoff mentioned previously.

C.2 Predicting Returns

Table C.4 presents the predictive regressions of our portfolio using the three risk perception indexes studied in the main section of this article.

Panels B and C of table C.4 show that independently of the data treatment, the VIX-EWZ and IVol-BR present no predictive power over the returns of providing liquidity.

Panel A shows that depending on the data treatment, changes in the EMBI+ present predictive capabilities over the returns on providing liquidity. Table C.4 Panel A columns (2) to (6) represent the portfolios built by increasingly removing data using minimum levels of the average monthly volume. Portfolios (4) to (6) present the most significant coefficients while (2) and (3) bear higher returns, but does not appear to be as predictable. When adding the control variable to the equation, only portfolio (6), with the most restrictive of filters, still generates a statistical significance of 95% but also bears the lowest return of this class of filters. Columns (7) to (11) represent portfolios built by increasingly removing data using minimum monthly volume present similar results in that when filters are too lax as in (7) and (8), returns are higher but unpredictable where predictability increases and return decreases when the filters become more strict. The same is also reflected in columns (12) to (16) that increasingly remove data using maximum excess return.

These results indicate that for this strategy, either there is i) a trade-off between returns and predictability, or ii) that our data removal procedure is not efficient. In more volatile and less liquid markets such as Brazil, when aiming at predictability, the portfolio construction should also use traded volume to construct the weight on each stock, as was done in Pástor and Stambaugh (2003), which would lead to a less intense effect of outlier returns in the portfolio due to idiosyncratic price corrections which we aimed to remove with the mentioned filters above.

Table Data Treatment

This table represents the daily regression on different reversal portfolios calculated with transaction prices where the dependent variable is the reversal strategy return on day t (in percent), and the predictor variables are measured at the end of day t - 5. VX EWZ and IVOL-Br are normalized to a daily volatility measure by dividing it by $\sqrt{2}50$. The variable used in the EMBI+ Brazil is the percentual changes of the index. The control variables RM is the lagged four-week return on the value-weighted of the chosen B3 stocks. Standard errors are reported in parentheses. The significance of the regressor is reflected by the color. There are three tones of green and each color reflects either a coefficient significance of 95%(light green), 99% (medium green), or 99,9%(strong green). Each column represents a portfolio constructed by applying different data removal filters as described in Table C.1

	Portfolios																
	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
									EMBI +								
Intercept	0,00479	0,00203	0,00179	0,00097	-0,00082	0,00060	0,00064	0,00148	0,00110	0,00096	0,00087	-0,00599	0,00165	0,00160	0,00132	0,00102	0,00058
	(0,00041)	(0,00037)	(0,00017)	(0,00011)	(0,00010)	(0,00010)	(0,00009)	(0,00013)	(0,00012)	(0,00011)	(0,00011)	(0,00010)	(0,00012)	(0,00010)	(0,00008)	(0,00007)	(0,00006)
EMBI +	0,00587	0,00884	0,00717	0,00899	0,01085	0,01066	0,00908	0,00822	0,00723	0,00896	0,01067	0,01059	0,00488	0,00580	0,00728	0,00522	0,00535
	(0,01445)	(0,01322)	(0,00605)	(0,00396)	(0,00366)	(0,00345)	(0,00313)	(0,00461)	(0,00405)	(0,00396)	(0,00372)	(0,00345)	(0,00422)	(0,00640)	(0,00298)	(0,00248)	(0,00219)
Adj. R2	-0,00017	-0,00011	0,00008	0,00085	0,00158	0,00173	0,00150	0,00044	0,00044	0,00838	0,00147	0,00215	0,00007	0,00039	0,00100	0,00070	0,00101
Intercept	0,05074	0,00216	0,00194	0,00110	0,00092	0,00067	0,00071	0,00162	0,00123	0,00109	0,00097	0,00067	0,00175	0,00171	0,00146	0,00108	0,00060
	(0,00043)	(0,00039)	(0,00018)	(0,00012)	(0,00011)	(0,00010)	(0,00009)	(0,00013)	(0,00012)	(0,00012)	(0,00011)	(0,00010)	(0,00012)	(0,00010)	(0,00009)	(0,00007)	(0,00006)
EMBI +	0,00041	0,00617	0,00401	0,00599	0,00845	0,00895	0,00763	0,00499	0,00412	0,00603	0,00840	0,00888	0,00273	0,00344	0,00505	0,00355	0,00453
	(0,01465)	(0,01340)	(0,00614)	(0,00401)	(0,00372)	(0,00350)	(0,00318)	(0,00467)	(0,00411)	(0,00401)	(0,00377)	(0,00350)	(0,00428)	(0,00345)	(0,00302)	(0,00252)	(0,00222)
RM	-0,01708	-0,00829	-0,00953	-0,00877	-0,00695	-0,00493	-0,00418	-0,00913	-0,00879	-0,00829	-0,00642	-0,00487	-0,00608	-0,00668	-0,00630	-0,00482	-0,00278
	(0,00767)	(0,00698)	(0,00315)	(0,00202)	(0,00186)	(0,00174)	(0,00157)	(0,00225)	(0,00199)	(0,00194)	(0,00183)	(0,00171)	(0,00207)	(0,00167)	(0,00146)	(0,00123)	(0,00120)
Adj. R2	0,00064	-0,00003	0,00173	0,00448	0,00420	0,00315	0,00273	0,00350	0,00420	0,00432	0,00376	0,00315	0,00162	0,00384	0,00456	0,00358	0,00189
									VIX EWZ								
Intercept	0,00444	0,00137	0,00197	0,00119	0,00041	0,00030	0,00036	0,00146	0,00134	0,00119	0,00076	0,00029	0,00159	0,00175	0,00139	0,00131	0,00068
	(0,00143)	(0,00133)	(0,00121)	(0,00067)	(0,00066)	(0,00065)	(0,00053)	(0,00083)	(0,00069)	(0,00067)	(0,00067)	(0,00065)	(0,00065)	(0,00054)	(0,00045)	(0,00037)	(0,00030)
VIX EWZ	-0,00057	0,00008	-0,00016	-0,00019	0,00006	-0,00004	-0,00003	-0,00003	-0,00014	-0,00019	-0,00011	-0,00003	0,00000	-0,00077	-0,00002	-0,00013	-0,00004
	(0,00066)	(0,00062)	(0,00056)	(0,00031)	(0,00031)	(0,00030)	(0,00025)	(0,00038)	(0,00032)	(0,00031)	(0,00031)	(0,00030)	(0,00030)	(0,00025)	(0,00021)	(0,00017)	(0,00014)
Adj. R2	-0,00012	-0,00045	-0,00043	-0,00029	-0,00045	-0,00045	-0,00045	-0,00046	-0,00037	-0,00030	-0,00041	-0,00046	-0,00046	-0,00042	-0,00046	-0,00018	-0,00043
Intercept	0,00493	0,00158	0,00226	0,00139	-0,00056	0,00045	0,00044	0,00165	0,00149	0,00138	0,00093	0,00043	0,00172	0,00191	0,00154	0,00134	0,00076
	(0,00144)	(0,00134)	(0,00122)	(0,00068)	(0,00067)	(0,00066)	(0,00053)	(0,00084)	(0,00070)	(0,00068)	(0,00068)	(0,00066)	(0,00065)	(0,00054)	(0,00046)	(0,00037)	(0,00030)
VIX EWZ	-0,00071	0,00002	-0,00024	-0,00025	0,00001	-0,00008	-0,00006	-0,00008	-0,00019	-0,00025	-0,00016	-0,00007	-0,00003	-0,00013	-0,00006	-0,00015	-0,00007
	(0,00067)	(0,00062)	(0,00056)	(0,00031)	(0,00031)	(0,00030)	(0,00025)	(0,00039)	(0,00032)	(0,00031)	(0,00031)	(0,00030)	(0,00030)	(0,00025)	(0,00021)	(0,00017)	(0,00014)
RM	-0,01514	-0,00664	-0,00928	-0,00644	-0,00502	-0,00453	-0,00259	-0,00609	-0,00484	-0,00611	-0,00533	-0,00448	-0,00387	-0,00507	-0,00476	-0,00108	-0,00208
	(0,00716)	(0,00669)	(0,00604)	(0,00330)	(0,00323)	(0,00315)	(0,00255)	(0,00396)	(0,00329)	(0,00320)	(0,00318)	(0,00311)	(0,00307)	(0,00256)	(0,00215)	(0,00179)	(0,00161)
Adj. R2	0,00148	-0,00046	0,00020	0,00100	0,00021	0,00004	-0,00044	0,00017	0,00017	0,00093	0,00043	0,00004	-0,00019	0,00093	-0,00012	-0,00047	-0,00012
									Ivol-BR								
Intercept	0,00375	- 0,00288	0,00318	0,00047	- 0,00061	- 0,00051	- 0,00057	0,00201	0,00086	0,00046	0,00030	- 0,00053	0,00194	0,00109	0,00066	0,00087	0,00001
	(0,00192)	(0,00180)	(0,00161)	(0,00086)	(0,00083)	(0,00085)	(0,00075)	(0,00095)	(0,00090)	(0,00086)	(0,00084)	(0,00085)	(0,00086)	(0,00075)	(0,00063)	(0,00051)	(0,00042)
Ivol-BR	-0,00015	-0,00082	-0,00096	0,00021	0,00076	0,00054	0,00057	-0,00030	0,00013	0,00021	0,00015	0,00055	-0,00015	0,00038	0,00048	0,00009	0,00039
	(0,00127)	-(0,00119)	(0,00107)	(0,00057)	(0,00055)	(0,00057)	(0,00050)	(0,00063)	(0,00060)	(0,00057)	(0,00056)	(0,00057)	(0,00057)	(0,00050)	(0,00042)	(0,00034)	(0,00028)
Adj. R2	-0,00052	-0,00028	-0,00011	-0,00046	0,00046	-0,00006	0,00018	-0,00041	-0,00051	-0,00046	-0,00049	-0,00002	-0,00049	-0,00022	0,00015	-0,00049	0,00052
Intercept	0,00443	0,003066	0,00359	0,00068	-0,000467	-0,000399	-0,000455	0,00218	0,0010155	0,000657	0,00049	-0,000428	0,002035	0,001357	0,000929	0,0009381	0,0000713
	(0,00197)	(0,00185)	(0,00165)	(0,00088)	(0,00086)	(0,00087)	(0,00077)	(0,00097)	(0,00092)	(0,00088)	(0,00086)	(0,00087)	(0,00089)	(0,00077)	(0,00065)	(0,00052)	(0,00043)
Ivol-BR	-0,00051	-0,00092	-0,00118	0,00009	0,00068	0,00048	0,00051	-0,00039	0,00003	0,00010	0,00004	0,00050	-0,00020	0,00023	0,00033	0,00005	0,00035
	(0,00130)	(0,00122)	(0,00109)	(0,00058)	(0,00056)	(0,00058)	(0,00051)	(0,00064)	(0,00061)	(0,00058)	(0,00057)	(0,00057)	(0,00058)	(0,00051)	(0,00043)	(0,00035)	(0,00029)
RM	-0,01094	-0,00308	-0,00680	-0,00353	-0,00225	-0,00177	-0,00193	-0,00274	-0,00246	-0,00325	-0,00304	-0,00172	-0,00157	-0,00433	-0,00435	-0,00105	-0,00088
	(0,00748)	(0,00704)	(0,00624)	(0,00327)	(0,00315)	(0,00320)	(0,00279)	(0,00350)	(0,00333)	(0,00317)	(0,00311)	(0,00315)	(0,00318)	(0,00277)	(0,00233)	(0,00191)	(0,00176)
Adj. R2	0,00008	-0,00071	0,00001	-0,00037	0,00020	-0,00042	-0,00010	-0,00061	-0,00075	-0,00043	-0,00052	-0,00039	-0,00090	0,00055	0,00147	-0,00087	0,00012

Bibliography

[1] GORTON, GARY, AND ANDREW METRICK. **Haircuts**. Federal Reserve Bank of St. Louis Review, 92:507–519, 2010.

[2] GROSSMAN, SANFORD J., AND MERTON H. MILLER. **Liquidity and market structure**. Journal of Finance, 43:617–633, 1988.

[3] HENDERSHOTT, TERRENCE, CHARLES M. JONES, AND ALBERT J. MENKVELD. **Does algorithmic trading improve liquidity?** Journal of Finance, 66:1–33, 2011.

[4] KANIEL, RON, GIDEON SAAR, AND SHERIDAN TITMAN. **Individual investor trading and stock returns**. Journal of Finance, 63:273–310, 2008.

[5] STEFAN NAGEL. **Evaporating liquidity**. The Review of Financial Studies, 25:2005–2039, 2012.

[6] LEHMAN, BRUCE N.. **Fads, martingales, and market efficiency**. Quarterly Journal of Economics, 105:1–28, 1990.

[7] LO, ANDREW W., AND A. CRAIG MACKINLAY. **When are contrarian profits due to stock market overreaction?** Review of Financial Studies, 2:175–205, 1990.

[8] PASTOR, LUBOS, AND ROBERT F. STAMBAUGH. **Liquidity risk and expeced stock returns**. Journal of Political Economy, 111:642–685, 2003.

[9] HAMEED, ALLAUDEEN, WENJIN KANG, AND S. VISWANATHAN. **Stock market declines and liquidity**. Journal of Finance, 65:257–293, 2010.

[10] ADRIAN, TOBIAS, AND HYUN SONG SHIN. **Liquidity and leverage**. Journal of Financial Intermediation, 19:418–437, 2010.

[11] ANG, ANDREW, SERGIY GOROVYY, AND GREGORY B. VAN INWEGEN. **Hedge fund leverage**. Journal of Financial Economics, 102:102–126, 2011.

[12] COMERTON-FORDE, CAROLE, TERRENCE HENDERSHOTT, CHARLES M. JONES, PAMELA C. MOULTON,AND MARK S. SEASHOLES. **Time**

variation in liquidity: The role of market makerinventories and revenues. Journal of Finance, 65:295–331, 2010.

[13] HENDERSHOTT, TERRENCE, AND ALBERT J. MENKVELD. **Price pressures**. Journal of Financial Economics, 114:405–423, 2014.

[14] HASBROUCK, JOEL. **The summary informativeness of stock trades: An econometric analysis**. Review of Financial Studies, 4:571–595, 1991.

[15] HANSCH, OLIVER, NARAYAN Y. NAIK, AND S. VISWANATHAN. **Do inventories matter in dealership markets? evidence from the london stock exchange**. Journal of Finance, 53:1623–1656, 1998.

[16] WANG, JIANG. **A model of competitive stock trading volume**. Journal of Political Economy, 102:127–168, 1994.

[17] LLORENTE, GUILLERMO, RONI MICHAELY, GIDEON SAAR, AND JIANG WANG.. **Dynamic volumereturn relation of individual stocks**. Review of Financial Studies, 15:1005–1047, 2002.