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Investigation of Stochastic Pairs Trading Strategies Under Different Volatility Regimes

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Abstract. We investigate several market-neutral pairs trading strategies and find evidence that market-neutral equity trading outperforms various stock indices in 2008, the first full year of the global financial meltdown. We use fourteen distinct market-neutral trading strategies, using combinations of seven trading methods and two selection methods of pairs trading.

Keywords. Stochastic Stationarity, Granger-Causality, Vasicek Stochastic Differential Equation, Generalized Method of Moments, Risk Management, Market Neutral Trading, Pairs Trading, Financial Crisis.

AMS subject classification: 62P20, 62M10, 62M20, 60G10, 91B70, 91B60, 91B84, 91B24, 91B25, 91B30

1 Introduction

Market-neutral equity trading strategies exploit mispricings in a pair of similar stocks [1]. Mispricings have been found to be more common during a global financial crisis [10]. Therefore, more possibilities emerge at bad times. Moreover, there are fewer market participants out there, which reduces competition. Therefore, it is not surprising that market-neutral trading performs well during most severe market conditions. In this paper, we propose several market-neutral equity trading strategies and find empirical evidence for the above statement.

We propose several market-neutral equity trading systems (a.k.a. pairs trading) and show that not only do they outperform existing systems, but they also beat the global financial crisis of 2008 by bringing in more than 40% net annual return on average. Each and every one of selected market-neutral equity trading systems utilizes a combination of well-known tools of econometrics to select market-neutral pairs. These are Augmented Dickey-Fuller (ADF) [5] and Granger-Causality Tests [12] along with Beta calculation in order to select market-neutral pairs. Furthermore, we employ the Vasicek Stochastic Differential Equation [21] for modelling the dynamics of the ratio of prices of a pair of stocks, and Generalized Method of Moments,[13] a nonparametric method, for parameter estimation of the Vasicek Method. On top of these, we investigate a very simple trading strategy that proves to be low-risk and high-return seen from the perspective of our disjoint training and backtesting results that span 10 years ending on the last trading day of December 2008.

The seminal pairs trading implementation was developed in the late 1980s by quantitative analysts led by Gerald Bamberger at Morgan Stanley. Pairs trading is a well-known trading idea that involves taking one long and one short position in two assets A and B whose prices P_A and P_B are believed to have a ratio $R_t = (P_A/P_B)$ that is mean-reverting over time. If, for instance, the spread $(P_A - P_B)$ is much greater than usual, then one would expect it to diminish in such a way as to make the ratio to return to its long term average, θ. Taking a long position in asset B along with a short position, with an equal dollar amount, in asset A constitutes a pair-trade. The coveted property of this $(-A, B)$ pair-trade is that no matter which direction the market goes, once R_t returns to θ, the trade is closed with a profit.

One of the most notable papers on pairs trading is written by Gatev, Goetzmann, and Rouwenhorst [10], which offers a comprehensive analysis. The authors use daily US data from 1962 to 2002 and show that a simple pairs trading rule produces excess returns of 11% per annum and a monthly Sharpe ratio which can be up to six times larger than market returns. It is shown that the returns have high risk-adjusted alphas, low exposure to known sources of systematic risk, cover reasonable transaction costs, and do not come from contrarian relative-price momentum strategies as documented in Lehmann [18]. However, the returns are comparable in magnitude to relative-price momentum strategies explained in Jegadeesh and Titman [15]. Gatev et. al. interpret pairs trading profits as pointing towards a systematic dormant factor relating to the agency costs of professional arbitrage. Minimum distance criterion, based on 'Law of One Price', is proposed as a metric to selecting the best pairs. It is argued that the important economic principle of the 'Law of One Price' explains these arbitrage profits. The information period length is determined to be a constant 60 days.

Kovajecz and Odders-White [17] link such high returns with market making trading activities, which allow price discovery of the underlying securities. Avellaneda and Lee [3] on the other hand, focus on investigating two different trading signals in constructing Principal Component Analysis based and ETF based strategies. Also, regarding the trading volumes of stocks, the paper analyzes the performance of these statistical arbitrage strategies. As in Gatev et. al., the information period length is determined to be a constant 60 days. Mostly focusing on the selection criteria of pairs, Vidyamurthy [22] and Herlemont [14] propose the use of cointegration [9]. Elliott, Hoek and Malcolm [7] explicitly model the mean reversion process of the difference between the prices of paired stocks in continuous time. Finally, Perlin [19] finds that pairs trading is profitable at the Brazilian Market.

Of course, the risk that one takes when entering a pair-trade is the possibility of a structural breakdown of the mean-reverting-ratio property. In this paper, we construct pairs while taking into account this possibility as well. We describe efficient methods for selecting pairs and then discuss rules for entering and exiting pairs trades.

A well-constructed pairs trading system needs to possess the following four basic properties:

- A reliable pair selection criterion
- An efficient stochastic model to mimic the motion of a given pair
- A good parameter estimation technique for the stochastic model
- A low-risk high-return trading strategy with the given pair(s)
- A comprehensive backtesting methodology using disjoint training and testing data going back at least 10 years.

Our methodology includes the following components:

- We propose a number of new market-neutral pair selection rules where we pick the best 5 pairs that pass different combinations of the Augmented Dickey-Fuller Test, two-way Granger-Causality Test and the Market Factor Ratio (MFR) test, which we define later in the paper.
- We employ Generalized Method of Moments, a non-parametric method, for parameter estimation of the Vasicek Model in market-neutral trading for the first time. Note that the Vasicek model has been used in pairs trading earlier in an unpublished paper [6]. However, its parameters were estimated with a *parametric* method.
- We provide portfolio performance results for the global financial crisis year of 2008 using 14 different market-neutral trading algorithms and show that these algorithms perform significantly better in 2008 than they do in the less volatile years between 2001 and 2007.

2 Selection Strategies

Constructing a profitable trading strategy always starts with the comprehensible sifting of investment options. In this paper, four types of quantitative selection techniques and their combinations will be discussed: Minimum Distance Method, Augmented Dickey Fuller Test, Two-Way Granger Causality Test and the Market Factor Ratio Method.

2.1 Minimum Distance Method

Gatev, Goetzmann and Rouwenhorst [10] test their pairs trading system over daily S&P500 data dating from 1962 to 2002. They select pairs of stocks using the minimum distance method. The main idea to their selection criterion is to select pairs which have had similar historical price moves. According to the Law of One Price [2], similar securities should have similar prices. To start the process, it is assumed that all prices are equal to 1.00 for the starting day. Then, a cumulative return index is generated for all stocks. To select pairs from this data set, sum of squared deviations is used:

$$\gamma(X, Y) = \sum_{t=1}^{T} (C_X^t - C_Y^t)^2 \tag{1}$$

where C_X^t and C_Y^t are the cumulative return indices for assets X and Y at time t. The smaller value of $\gamma_(X, Y)$ gives us the information that selected stocks have had similar price changes until time T.

2.2 Augmented Dickey Fuller Test

In order to generate a profit in a pair-trade, the ratio of the prices, R_t needs to have both a constant mean and a constant volatility over time. We use the well-known unit root test to check for weak stationarity, the existence of which proves that we have what we are looking for. For an autoregressive process $AR(1)$ such as $\delta X_t = (\phi_1 - 1)X_{t-1} + \varepsilon_t$, and defining $a \equiv (\phi_1 - 1)$ the unit root test can be written as follows

$$H_0 : a = 0$$
$$H_1 : a < 0$$

The term "augmented" comes from the number of lagged values of the dependent variable [5]. The number of lagged difference terms to include is determined empirically, the idea being to include enough terms so that the error term in the tested equation is serially uncorrelated. Tau Statistics will be used to determine the passing pairs.

2.3 ADF Test combined with two-way Granger Causality

Our top concern is the risk that one takes when entering a pairs position, which is the possibility of a structural breakdown of the mean-reverting-price-ratio property. This paper tries to minimize this risk by using Granger

Causality tests as described below and by also employing an ad hoc trade time-out date, which is the last trading day of the selected year.

This is how we choose the pairs: Note that the ADF test for R_t gives one of only two results, Pass or Fail. This means that we cannot sort the Tau Statistics as we did in the Minimum Distance Method. Because there are too many pairs that pass the ADF test, we employ Granger Causality to pick our final set of pairs.

As is well-known, Granger-causality does not mean causality in the logical sense. Rather, "P_A Granger-causes P_B" means the former can be used to predict the latter. Obviously, two-way Granger-causality is stronger than one-way Granger-causality. We surmise that a pair selected as such makes it less likely for the aforementioned structural breakdown to take place before the trade times out at the end of the year.

2.4 Market Factor Ratio (MFR)

One long and one short position $(-A, B)$, do not necessarily lead to a market-neutral strategy. We investigate a method to measure the degree of market-neutrality of a pair. This is done by picking pairs that have highly similar market exposures, or betas. The closer the betas are, the better the market-risk hedging is [8]. We generate a Market Factor Ratio (MFR) criterion for each possible pair:

$$MFR = abs(\frac{\beta_1}{\beta_2}) - 1 \tag{2}$$

The MFRs are listed in increasing order, and the top 5 market-neutral pairs are selected from this list. We choose the top 5 because we want to make a fair comparison with other pairs trading strategies, which also use a quota of 5, the industry standard.

3 Trading Algorithms

3.1 The Two Standard Deviation Rule

Let μ_t be the moving average and s_t be historical volatility (moving standard deviation) of the ratio R_t at time t. As expressed in [10], traders generally use a rule of thumb, namely the two-standard-deviation rule, in entering a pair-trade (-A,B) or (A, -B). The idea is to open the pair-trade when R_t increases (or diminishes) and hits the two-standard-deviation barrier $\mu_t + 2s_t$ (or $\mu_t - 2s_t$) and to close it when R_t returns to its moving average. We use the shorthand notation $(2STD)$ for this specific trade rule. It is clear that this overly simplistic rule can be optimized by using more sophisticated quantitative tools. One such tool is to employ the Vasicek Stochastic Differential Equation model for R_t.

3.2 Implementation of Vasicek Model to Pairs Trading

In our market-neutral trading system, instead of using the moving average and historical volatility of R_t, we use θ and σ, the long-term mean and instantaneous standard deviation, respectively, obtained by applying a Vasicek model to R_t. We estimate fresh values of θ and σ at every time step (every week) along the way.

Our research investigates a Vasicek Model based trading system that uses the two-standard deviation rule to open a trade. (We use the shorthand notation $(V2STD)$ for this specific trade rule.) That is, we open the trade $(-A, B)$ when $R_t \geq \theta + 2\sigma$. We close this trade when $R_t \leq \theta$. Likewise, we open the trade $(A, -B)$ when $R_t \leq \theta - 2\sigma$. We close this trade when $R_t \geq \theta$.

Mean reversion is a tendency for a stochastic process to remain near, or tend to return over time to its long-run mean. As well-known examples, interest rates and implied volatilities can be given. In general, stock prices themselves do not tend to have mean-reversion. The Vasicek model [21] is generally used for interest rate modeling, but it can easily be applied to other mean-reverting processes as well. This model assumes that a mean-reverting process has the stochastic differential equation in the form of:

$$dR_t = \kappa(\theta - R_t) + \sigma dW_t \tag{3}$$

where W_t is a Wiener process that models the continuous randomness of the system. θ is the long-term mean around which all future trajectories of R_t will evolve. κ is the speed of mean reversion. A very high κ can lead to fewer trading opportunities, whereas a very low one can lead to a more risky trading structure. σ is the instantaneous volatility, a very high value of which may easily lead to a risky trading system.

The evolutions of these parameters are of importance. When we solve the stochastic differential equation, we obtain

$$R_t = R_0 e^{-\kappa t} + \theta(1 - e^{-\kappa t}) + \sigma e^{-\kappa t} \int_0^t e^{\kappa s} dW_s \tag{4}$$

The expected value is given by

$$E[R_t] = R_0 e^{-\kappa t} + \theta(1 - e^{-\kappa t}) \tag{5}$$

Finally, the variance is

$$\frac{\sigma^2}{2\kappa}(1 - e^{2\kappa}) \tag{6}$$

Thus, the long-term mean is

$$\lim_{x \to \infty} E[R_t] = \theta \tag{7}$$

and the long-term variance is

$$\frac{\sigma^2}{2\kappa} \tag{8}$$

In order to visualize how the Vasicek model works for the pair BA - AXP see figures 1 to 8.

Figure 1: κ vs. θ

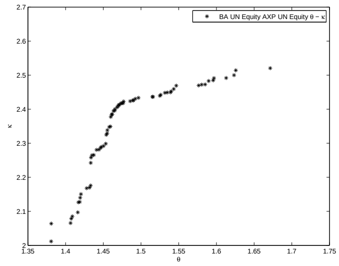


Figure 2: κ vs σ

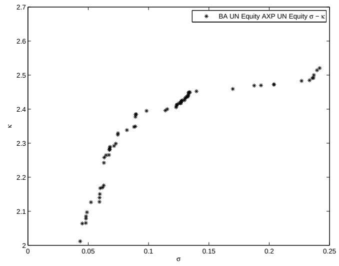
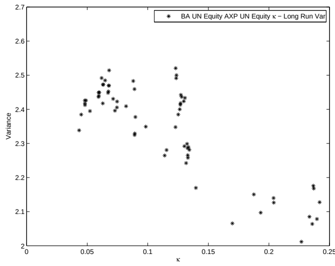


Figure 3: Long-term variance vs κ



Do, Faff and Hamza (2006) use Expectation Maximization [20] and Kalman Filter [16] to estimate Vasicek parameters for a pairs trading system. However, this choice requires the need to make an assumption about the distribution of parameters. In our system, we do not make any such assumptions since we use The Generalized Method of Moments, a nonparametric model.

Figure 4: κ vs time

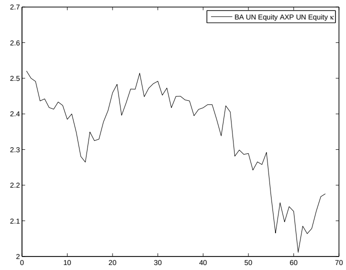


Figure 5: θ vs time

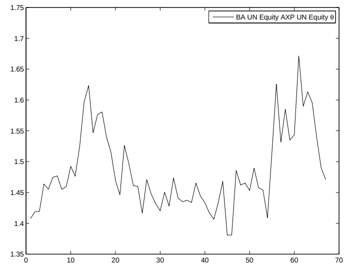


Figure 6: σ vs time

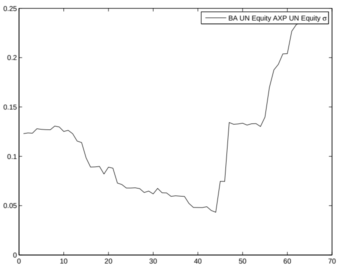


Figure 7: Long-term variance vs time

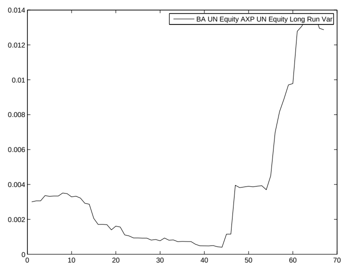
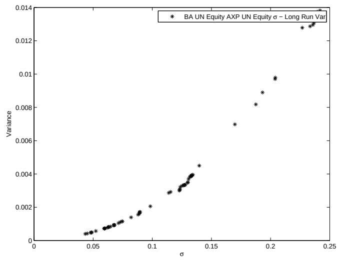


Figure 8: Long-term variance vs σ



4 GMM Estimation Technique

To explain the dynamic properties of econometric systems, parameter estimation procedures have crucial importance. The Generalized Method of Moments (GMM) was first introduced by Lars Hansen [13]. GMM is a flexible tool employed in a large number of econometric and economic models. Theoretically, it provides a general framework for considering issues of statistical consequence because it entails the solution to finding many estimators of interest in econometrics. Unlike methods such as maximum likelihood estimation, it generates a computationally feasible method of estimating nonlinear dynamic models without making any assumptions on the probability distribution of the data. The only necessary inputs for GMM are the first few moments derived from the underlying model. This property makes GMM very useful in areas like macroeconomics, finance, agricultural economics, environmental economics, and labor economics.

To estimate the parameters of the Vasicek model explained earlier, we use GMM estimation. Our trading system shall include the parameters θ and σ to make the trade decisions.

We assume modeling the ratio R_t with the Vasicek model and estimating the parameters θ and σ will give us dynamic information on the behavior of the pairs. (In order to compute the former two parameters, κ also needs to be estimated because it is one of the unknowns of the nonlinear GMM system.)

To discretize the continuous Vasicek stochastic equation, the following steps are implemented, [21] The continuous time model is restated as,

$$dR_t = \kappa(\theta - R_t) + \sigma dW_t \tag{9}$$

where, R_t is the real data (the ratio of the selected pairs at a selected time t). So,

$$E[dR_t] = \kappa(\theta - R_t)dt \tag{10}$$

A discrete time approximation is

$$R_t - R_{t-1} = \kappa(\theta - R_{t-1})(t - (t-1)) + \epsilon_t \tag{11}$$

Let $Y_t = R_t - R_{t-1}$ and $S = -\kappa$ and $Q = -S\theta$. Thus,

$$Y_t = \frac{1}{52}(Q + SR_{t-1}) + \epsilon_t \tag{12}$$

Note that we use $\frac{1}{52}$ for $t-(t-1)$ because we use weekly data. So,

$$e_1(t) = \frac{1}{52}(Q + SR_{t-1}) \tag{13}$$

$Var[dR_t] = \sigma^2 dt$. Because, $E[dW_t^2] = dt$

$$e_2(t) = e_1^2(t) - \frac{\sigma^2}{52} \tag{14}$$

And g is defined as :

$$g = [e_1, e_2] \tag{15}$$

Now, the goal is to estimate the unknown parameters, Q, S and σ by minimizing the quadratic form $g^T W g$, where W is a weight matrix that considers the variances of the moments and gives more positive weighting to the component of g that has a smaller variance. The optimization is done iteratively, using the fmincon function of MATLAB. This function is an efficient optimizer for nonlinear systems with constraints.

5 Application Methodology

This section describes the methodology used for the analysis in this paper. First, it introduces the disjoint training and testing periods used in the experiments, then it introduces the algorithms used for pair selection and trading.

5.1 Training and Testing Periods

We first define two consecutive time periods as Training and Testing. The training period is a preselected period where the parameters of the experiment are calculated and frozen. Immediately after the training period, the testing period follows, where we run the experiments with these frozen parameters. Note that pairs are also treated as parameters in our trading system. We use one year for training and the consequent year for testing.

In our analysis, we first select pairs and then make trading decisions using one step ahead (one week ahead) estimates of the parameters of the underlying Vasicek model. To generate a one-step ahead forecast, we need to specify a fixed moving window length similar to a window length used in calculating moving averages.

Consequently, our training period needs to find answers to two questions:

- What are the best pairs for trading?

- What is the optimum window length?

We first select pairs with a selection algorithm and then calibrate the optimum window length. That is, we scan the same training period twice, once for pair selection and once for window length optimization.

We select pairs by a combination of the following methods mentioned earlier: Minimum Distance Method (MDM), Market Factor Ratio (MFR), Augmented Dickey-Fuller Test (ADF), and the two-way Granger Causality Test, abbreviated as (G). We use + (plus) sign for a combination of two methods.

In the final tally, we employ seven different methods: {MFR}, {ADF+G+MFR}, {ADF+MFR}, {G+MFR}, {G}, {ADF+G}, and {MDM}. Note that for all selection methods that involve {MDM} or {MFR}, we select the top 5 pairs from a sorted list of minimum distance or minimum market factor ratio, respectively, and create an equally weighted portfolio in each case. For selection methods involving {G}, but not {MFR}, the top 5 passing pairs are selected, where the sort is based on the sum of p-values of the two-way Granger Causality Tests.

Window length optimization is actually an optimization based on profit. With each selected pair, we trade with 24, 36, 48, 60 and 72 weeks of window length in training period. The window length with the highest cumulative profit is selected as the optimum.

We also have a trade-time out date, which is the last trading day of each year. Once the trade time-out date is reached, the pair trade is closed no matter what the profit or loss is. The industry has similar time-out mechanisms. A pair trade is closed if a certain amount of time has passed or a certain fixed date is reached.

Note that we do not employ any stop-loss or take-profit parameters, which is not the usual way the industry does pairs-trading. Most of the time, the industry uses ad hoc rules for stop-loss and take-profit.

6 Experiments and Analysis

6.1 Data and Coding Infrastructure

We have downloaded end-of-week price data for stocks that comprise the Dow Jones 30 (DJ30) index[1] from Thompson Reuters Datastream [4]. In all our experiments, the weeks between the last trading day of the 26th week of the year, N and the last trade date of the year, $(N + 1)$ are selected as the training period, whereas the weeks between Jan 2, $(N+2)$ and Dec 30, $(N+2)$ comprise the testing period, where $N = 1999, ..., 2006$. As mentioned before, we use weekly data and select pairs from stocks that comprise the Dow Jones 30 (DJ30) index. Consequently, we do the analysis for $\binom{30}{2} = 435$ possible pairs.

6.2 Results from Each of the Selection Methods

For our improvement on the ADF test, {ADF+G}, we record that, 15% of the possible total pairs pass the ADF test, but only 12% of these achieve successful results in the two-way Granger Causality test (though not all managed to make the quota of five.) Thus, the percentage of the pairs that pass both the ADF and the two-way Granger Causality is only 1.8%. Also, note that in 88% of the pairs selected by the ADF test, the stationarity of the price ratio R_t is reinforced by only *one* component of the pair, whereas in the remaining 12%, it is reinforced by both members.

The pairs that are selected by each pair selection method is given in Tables 1 to 7. The number of distinct pairs selected by 7 selection methods is given in Table 8. Also, the industries of the selected pairs are listed in the Appendix.

7 Results of the Trading Methods

After selecting the pairs in training period, we run a profit based window length optimization for each trading system as we discussed earlier. Once optimum window length is determined, we start trading with each of these portfolios. We use two different trading algorithms, namely the two-standard-deviation rule (2STD) and Vasicek-Model-Calibrated two-standard-deviation rule (V2STD). The cumulative profit of each portfolio for each algorithm are shown in Figures 9 and 10.

The following four tables show the annual net returns (net in the sense that *only* the average annual U.S. riskfree rate [11] is deducted) and the Sharpe Ratios for each trading market-neutral trading system.

[1] Note that, after this data set was decided upon, two members of DJ30 were replaced by others. On June 8, 2009, GM and Citigroup were replaced by The Travelers Companies and Cisco Systems, respectively.

Table 1: Augmented Dickey Fuller Test - Granger Causality Selection Results

Year	**Pair1**	**Pair2**	**Pair3**	**Pair4**	**Pair5**
2001	JPM-AA	JNJ-C	DIS-DD	CVX-BAC	XOM-AXP
2002	MSFT-MMM	MSFT-DD	MSFT-C	MSFT-AA	T-KO
2003	IBM-BA	CVX-BA	UTX-DD	INTC-HD	GE-BA
2004	UTX-BA	PG-IBM	MSFT-BAC	PFE-DD	T-BAC
2005	JNJ-BAC	JPM-AA	MCD-DIS	MCD-DD	DIS-AXP
2006	VZ-DIS	IBM-CVX	PG-AXP	JPM-BA	XOM-IBM
2007	INTC-GE	UTX-JNJ	INTC-IBM	JNJ-DIS	JNJ-INTC
2008	MRK-MCD	T-GE	PFE-AA	GE-CAT	**BA-AXP**

Table 2: Market Factor Ratio Selection Results

Year	**Pair1**	**Pair2**	**Pair3**	**Pair4**	**Pair5**
2001	MMM-JPM	XOM-CVX	T-HPQ	HPQ-AXP	PG-MSFT
2002	CVX-C	T-PFE	HD-BA	T-GE	XOM-PFE
2003	UTX-AXP	VZ-C	MSFT-JPM	MSFT-AA	T-GE
2004	BAC-AXP	XOM-CVX	VZ-JPM	GE-AA	JPM-CAT
2005	WMT-PG	CVX-BA	DD-BAC	JPM-HD	MRK-JPM
2006	MSFT-HPQ	XOM-CVX	KO-DD	INTC-DIS	PFE-DIS
2007	KO-JPM	UTX-JNJ	CVX-CAT	DIS-AA	XOM-CAT
2008	WMT-JPM	HPQ-DD	XOM-CVX	HD-DIS	UTX-CAT

Table 3: Augmented Dickey Fuller Test - Sorted by MFR Selection Results

Year	**Pair1**	**Pair2**	**Pair3**	**Pair4**	**Pair5**
2001	JNJ-C	HPQ-HD	DD-C	T-C	JPM-HD
2002	HD-CVX	HD-C	PFE-DD	XOM-DD	DD-CVX
2003	UTX-AXP	VZ-C	CVX-BA	WMT-JNJ	PFE-C
2004	HPQ-DIS	JPM-HD	HD-BA	DD-BAC	UTX-BA
2005	UTX-AXP	DD-AXP	UTX-BAC	MCD-DIS	WMT-C
2006	C-BAC	XOM-PG	UTX-PG	WMT-BAC	UTX-AXP
2007	KO-JPM	UTX-JNJ	VZ-GE	MCD-HPQ	MMM-BA
2008	XOM-CVX	DD-BAC	MRK-MCD	GE-AA	JPM-DD

8 Conclusions

market-neutral trading strategies exploit market inefficiencies, or mispricings in a pair of similar stocks, which are more commonplace in a global crisis allowing more trading possibilities to emerge at bad times. Moreover, there are fewer market participants out there, which reduces competition. Therefore it is not surprising at all that market-neutral trading performs best during the most severe market conditions. In this paper, we have shown empirical proof that supports the above statement.

There were three other important conclusions to be drawn from our experiments:

Table 4: Granger Causality Test - Sorted by MFR Selection Results

Year	Pair1	Pair2	Pair3	Pair4	Pair5
2001	JNJ-C	HPQ-HD	XOM-PFE	JPM-DD	T-JNJ
2002	HD-C	MCD-BAC	T-CVX	VZ-CVX	T-KO
2003	CVX-BA	JPM-AA	JPM-GE	JPM-CAT	JPM-AXP
2004	CVX-BAC	VZ-CVX	UTX-BA	BA-AA	PFE-DD
2005	VZ-AA	MCD-DIS	WMT-C	XOM-JNJ	JPM-AA
2006	XOM-CVX	UTX-PG	UTX-AXP	KO-AXP	PG-AXP
2007	UTX-JNJ	XOM-JNJ	MMM-IBM	MSFT-AA	JPM-BAC
2008	MRK-MCD	T-GE	C-AA	JPM-AA	C-AXP

Table 5: Granger Causality Test Selection Results

Year	Pair1	Pair2	Pair3	Pair4	Pair5
2001	JPM-AA	JNJ-C	DIS-DD	CVX-BAC	MMM-DD
2002	MSFT-MMM	WMT-HD	WMT-UTX	UTX-MMM	MSFT-DD
2003	JPM-CAT	JPM-C	MRK-JPM	VZ-JPM	JPM-AA
2004	UTX-BA	MSFT-CVX	VZ-CVX	PG-IBM	BA-AA
2005	JNJ-BAC	JPM-AA	MCD-DIS	MCD-DD	DIS-AXP
2006	JPM-AA	XOM-CVX	VZ-DIS	WMT-AA	IBM-CVX
2007	INTC-GE	UTX-JNJ	IBM-HD	MMM-IBM	INTC-IBM
2008	MSFT-KO	MRK-MCD	C-AA	CAT-C	JPM-AA

Table 6: Augmented Dickey Fuller Test - Granger Causality -Sorted by MFR Selection Results

Year	Pair1	Pair2	Pair3	Pair4	Pair5
2001	JNJ-C	HPQ-HD	JPM-DD	HD-DD	MCD-AA
2002	HD-C	MCD-BAC	T-CVX	VZ-CVX	T-KO
2003	CVX-BA	GE-BA	UTX-DD	INTC-HD	IBM-BA
2004	UTX-BA	PFE-DD	MSFT-BAC	T-BAC	PG-IBM
2005	MCD-DIS	WMT-C	XOM-JNJ	JPM-AA	JNJ-BAC
2006	UTX-PG	UTX-AXP	PG-AXP	VZ-DIS	VZ-KO
2007	UTX-JNJ	JPM-BAC	WMT-UTX	DIS-DD	INTC-DIS
2008	MRK-MCD	T-GE	PFE-AA	GE-CAT	T-MMM

1) For our improvement on ADF test we have observed that, 15% of the possible total pairs passed the ADF test, but only 12% of them achieved successful results on the two-way Granger Causality test (though not all managed to make the quota of five.) Thus, the percentage of the pairs that passed both the ADF and the two-way Granger Causality was only 1.8%. In other words, in 88% of the pairs selected by the ADF test, the stationarity of the price ratio R_t was reinforced by only *one* component of the pair, whereas in the remaining 12%, it is reinforced by both members.

2) When we observe only the returns and not the Vasicek-based two-standard deviation ($V2STD$) trading rule is clearly better than the simple

Table 7: Minimum Distance Method Selection [10] Results

Year	**Pair1**	**Pair2**	**Pair3**	**Pair4**	**Pair5**
2001	DD-AA	CAT-AA	GE-AXP	KO-JNJ	WMT-CAT
2002	MMM-DD	T-MCD	XOM-DD	XOM-MMM	PFE-DD
2003	UTX-DD	VZ-C	XOM-WMT	MMM-BAC	XOM-CAT
2004	XOM-PG	C-AXP	PG-IBM	DIS-C	PG-CVX
2005	XOM-CVX	JNJ-BAC	VZ-BAC	GE-BAC	PFE-KO
2006	GE-BAC	C-BAC	GE-C	UTX-PG	T-HD
2007	GE-C	IBM-DD	IBM-AXP	UTX-JPM	PG-JNJ
2008	DIS-DD	MMM-IBM	XOM-UTX	XOM-HPQ	JPM-DD

Table 8: The number of distinct pairs selected by 7 selection methods.

	Six Methods	MDM	Overlap
2001	20	5	1
2002	21	5	2
2003	19	5	2
2004	18	5	1
2005	16	5	1
2006	19	5	2
2007	20	5	0
2008	19	5	1

two-standard deviation ($2STD$) trading rule when the performance criterion is the average return over 8 years. This statement was not true when the performance criterion was the Sharpe Ratio over 8 years (in which we used annual returns.)

3) In 2008, the first year of the global financial crisis, the pairs that were selected using some combination of the two-way Granger-causality rule and traded with the $V2STD$ rule outperformed all competing models considered in this paper, where the performance criterion was only the annual return. Note that more than 40% returns were observed in each and every one of these cases.

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Table 9: Average Annual U.S. Riskfree rates [11]

Year	2001	2002	2003	2004	2005	2006	2007	2008
r_f	3.91	1.67	1.12	1.34	3.19	4.96	5.05	2.10

Table 10: Net returns and Sharpe Ratios

	1	**2**	**3**	**4**
Year	MDM (2STD)	MDM (V2STD)	ADF+G(2STD)	ADF+G (V2STD)
2001	4.38	7.15	4.83	-5.30
2002	3.19	4.95	5.86	-0.38
2003	8.25	12.94	5.53	4.75
2004	3.93	5.13	2.63	2.73
2005	1.70	5.12	0.66	4.51
2006	-2.71	-9.68	4.61	8.71
2007	-2.45	-1.63	-4.45	6.53
2008	13.40	19.29	21.26	41.14
STD	5.32	8.70	7.36	14.13
AVE	3.71	5.41	5.12	7.84
SHARPE	0.70	0.62	0.70	0.55

Table 11: Net returns and Sharpe Ratios

5	**6**	**7**	**8**
MFR(2STD)	MFR(V2STD)	ADF+G+MFR(V2STD)	ADF+G+MFR(2STD)
-6.20	3.09	-3.97	-1.21
10.27	14.25	2.72	1.66
0.07	5.55	4.75	5.19
0.42	15.37	2.73	0.87
9.20	2.93	8.14	-0.52
-0.23	13.72	1.60	1.20
-4.29	-2.10	-4.48	-4.03
3.52	15.35	48.61	21.43
5.85	6.93	17.13	7.87
1.60	8.52	7.51	3.07
0.27	1.23	0.44	0.39

Table 12: Net returns and Sharpe Ratios

9	**10**	11	**12**
ADF+MFR(2STD)	ADF+MFR(V2STD)	G+MFR(2STD)	G+MFR (V2STD)
8.68	2.19	-1.84	-3.65
6.66	8.37	1.66	2.94
0.40	-2.42	2.86	7.20
3.62	2.97	-3.59	0.23
0.06	-0.42	1.83	6.54
-0.58	-4.24	-0.29	2.91
-0.17	2.55	3.00	6.83
14.96	23.72	16.31	57.97
5.55	8.81	6.05	19.69
4.20	4.09	2.49	10.12
0.76	0.46	0.41	0.51

Table 13: Net returns and Sharpe Ratios

	13	14
Year	G (2STD)	G (V2STD)
2001	-2.20	-3.83
2002	5.28	4.10
2003	0.39	-0.25
2004	-6.66	-0.70
2005	-4.64	2.86
2006	1.47	8.74
2007	-3.85	3.80
2008	20.06	41.09
STD	8.50	14.29
AVE	1.23	6.98
SHARPE	0.14	0.49

Figure 9: Cumulative Return Graphs of V2STD Trading Methods

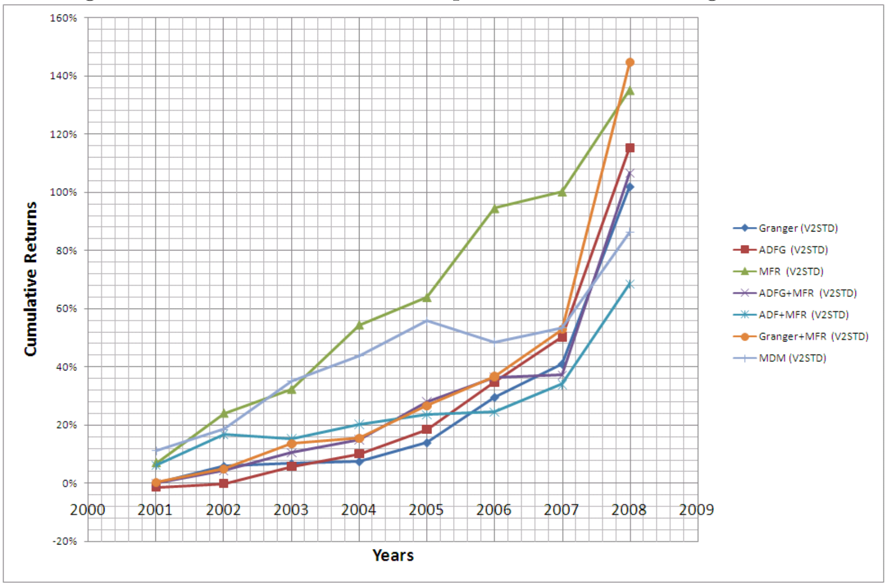
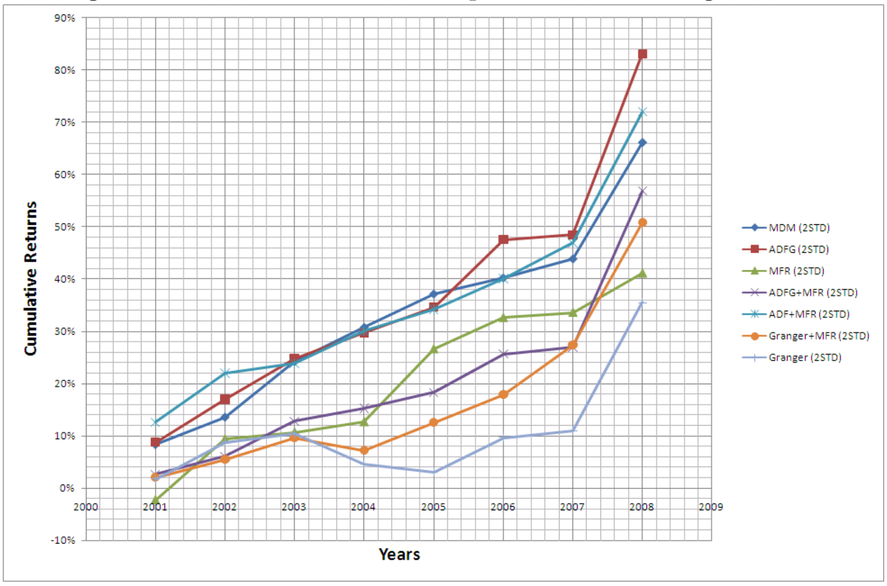


Figure 10: Cumulative Return Graphs of 2STD Trading Methods



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10 Appendix

Table 14: Members of the Dow Jones 30 Index

Symbol	Industry	Company
MMM	Conglomerate	3M
AA	Aluminum	Alcoa
AXP	Consumer finance	American Express
T	Telecommunication	AT&T
BAC	Banking	Bank of America
BA	Aerospace and defense	Boeing
CAT	Construction and mining equipment	Caterpillar
CVX	Oil & gas	Chevron Corporation
C	Financial services	Citygroup
KO	Beverages	Coca-Cola
DD	Chemical industry	DuPont
XOM	Oil & gas	ExxonMobil
GE	Conglomerate	General Electric
HPQ	Technology	Hewlett-Packard
HD	Home improvementretailer	The Home Depot
INTC	Semiconductors	Intel
IBM	Computersandtechnology	IBM
JNJ	Pharmaceuticals	Johnson & Johnson
JPM	Banking	JPMorgan Chase
KFT	Food processing	Kraft Foods
MCD	Fast food	McDonald's
MRK	Pharmaceuticals	Merck
MSFT	Software	Microsoft
PFE	Pharmaceuticals	Pfizer
PG	Consumer goods	Procter & Gamble
GM	Automotive	General Motors
UTX	Conglomerate	United Technologies Corporation
VZ	Telecommunication	Verizon Communications
WMT	Retail	Wal-Mart
DIS	Broadcasting and entertainment	Walt Disney

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