Statistical Arbitrage Trading Strategies and High Frequency Trading

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Abstract

Statistical arbitrage is a popular trading strategy employed by hedge funds and proprietary trading desks, built on the statistical notion of cointegration to identify profitable trading opportunities. Given the revolutionary shift in markets represented by high frequency trading (HFT), it is unsurprising that risks and rewards have changed. This paper explores the effect of HFT volume on statistical arbitrage profitability, and reports three trends in the data. First, higher levels of comovement due to HFT cause more stock pairs to be cointegrated over time. Second, profitability from statistical arbitrage remains steady among the vigintiles with the most HFT. Third, the range of profitability is larger in more recent years. These findings suggest that HFT increases correlation and volatility and has a direct impact on statistical arbitrage trading strategies.

Keywords: Statistical arbitrage, pairs trading, cointegration, high frequency trading

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1.0 Introduction

The trading of common stocks in the U.S. markets is now dominated by computer algorithms operating at sub-second speeds (Schapiro, 2010). This state of affairs represents the natural extension of quantitative strategies through the use of ever improving technology. One of the many available trading strategies that is ideally suited for such an application is statistical arbitrage, which involves forming a pair or portfolio of stocks whose relative pricing differs from their long-run equilibrium.

The roots of statistical arbitrage can be traced to the long-short mutual fund investment strategies of A. Winslow Jones in the 1950s. His idea was to use fundamental analysis to create a hedged portfolio of long and short positions to eliminate market risk. The return on the portfolio comes from the relative performance of the positions. So long as the long position gains more, or loses less, than the short position, the portfolio will be profitable. This can be true even in a mostly flat market, and the search for profits in difficult markets has made various incarnations of long-short investing popular since that time (Jacobs & Levy, 1993). Statistical arbitrage[1] is a quantitative application of this concept, based principally on price history (in addition to any screening traits for the candidate stocks for the portfolios).

The strategy gained prominence in the mid-1980s when Nunzio Tartaglia assembled a group of traders to create computer models that could efficiently access and analyze more data at faster speeds than previously possible. This timing reveals that pairs trading was among the earliest trading algorithms, replacing fundamental valuation, intuition, and trading skills with

[1]The term statistical arbitrage, as it is generally used, encompasses a range of investment strategies that share formal characteristics outlined in section two. When the long and short portfolios are restricted to a long position in just one stock and a short position in another, the implementation is often referred to as pairs trading, and both descriptive terms will be used interchangeably in this paper except where a distinction becomes necessary.

quantitative rules for a computer to check and implement. Early profitability also coincides with the faster trading and higher volumes in U.S. equity markets. Hence, it might be suggested that faster processing and more volume in equity markets would enhance profits for statistical arbitrage strategies.

High frequency trading (HFT, also used for high frequency traders) is widely acknowledged as a revolutionary and dominant force in equity markets and has grown at an astonishing pace to represent the majority of trading on the world's major exchanges (Curran & Rogow, 2009; Schapiro, 2010). Its new prominence has implications for market quality (Brogaard, 2010), the cost of transacting (Menkveld, 2012), liquidity (Hendershott, Jones, & Menkveld, 2011), price efficiency (Brogaard, Hendershott, & Riordan, 2011), correlation structure (Hanson & Muthuswamy, 2011), and a range of other effects in recent finance literature. It is unsurprising that such major market changes would impact the profitability of quantitative trading strategies.

Additionally, it is generally assumed that as knowledge of arbitrage opportunities becomes more widely dispersed, it becomes more difficult to profit from such strategies. However, some pricing anomalies continue to persist. Of particular relevance to pairs trading is the issue of contrarian profits (Jegadeesh & Titman, 1995). Profits from pairs trading might stem in part from investor over-reaction. One question this raises is whether HFT inhibits or promotes volatility and over-reaction that would enhance such profits. This question remains unresolved and widely disputed.

From the point of view of market efficiency, it would be logical that statistical arbitrage opportunities would decrease over time, especially as HFT took advantage of ever-smaller mispricings at ever-faster speeds. In theory, one could make a case for HFT as a force for decreased profitability or increased trading opportunities. Therefore, the principal contribution of this paper is an exploration of whether HFT increases or decreases the profits of statistical arbitrage trading strategies over time and across different levels of HFT volume.

The remainder of the paper proceeds as follows. The next section briefly reviews the literature related to both statistical arbitrage and HFT. Section three describes the data, the challenge of measuring HFT, and the pairs trading scheme. The fourth section presents results, and the fifth section concludes.

2.0 Literature Review

The trading strategy under consideration in this paper concerns the intersection of two topics: statistical arbitrage and high frequency trading. The pairs trading phenomenon has been well known for some time and spawned a range of papers on its profitability, in addition to implementation in industry. This section briefly reviews some of the major papers on the topic of pairs trading. Following that, we discuss the possible changes in the profitability of pairs trading in a high frequency trading environment. We are aware of only one other paper (Bowen, Hutchinson, & O'Sullivan, 2010) that has explored this overlap. That research closely examines the sensitivity of pairs trading profits to transaction costs and speed of execution.

Our work differs in several ways. First, the research question is whether stocks with different HFT volume behave differently in terms of the profitability of a statistical arbitrage trading scheme. The examination is a comparison of profitability across HFT volume vigintiles, rather than costs and speed across the entire universe of stocks. Second, the sample period under consideration here is considerably larger. Finally, Bowen, Hutchinson, and O'Sullivan (2010) employ a sum of squared deviations ranking, rather than cointegration testing, as employed in our study. The details of our trading scheme are delayed until section three.

2.1 Statistical Arbitrage Strategies

Statistical arbitrage is a strategy that attempts to profit from relative mispricing based on historical price patterns. Unlike true arbitrage, it is not riskless. Bondarenko (2003) defines a statistical arbitrage opportunity as a zero-cost trading opportunity for which the average expected payoff is nonnegative. In other words, the strategy must have an expectation of profit at inception, but losses are possible *ex post*. The definition is extended by comparison to standard option pricing models by Hogan, Jarrow, Teo, and Warachka (2004). In their work, a statistical arbitrage opportunity remains self-financing and zero-cost as well as satisfying four conditions: the discounted profit at inception is zero, and in the limit over a time span approaching infinity the expected profit is positive, the probability of loss is zero, and finally the time-averaged variance converges to zero when there is a positive probability of loss at all times.

True implementation of these formal definitions of statistical arbitrage requires continuous time rebalancing, in the spirit of the Black-Scholes option pricing model. In empirical work and industry practice, it is more typical for the long-short ratio to be fixed for a given trading period (e.g., Whistler, 2004). This introduces additional risk but limits transaction and monitoring costs considerably. Furthermore, it simplifies the actual trading strategy and moves the focus of research toward the task of identifying pairs that are likely to be profitable.

Previous research has utilized three main methods for identifying candidate pairs. First, the distance method ranks pairs by the sum of squared differences between the normalized price series (Gatev, Goetzmann, & Rouwenhorst, 2006). Second, the stochastic spread approach was proposed by Elliot, van der Hoek, and Malcolm (2004). This work models the spread explicitly in a continuous time setting, which is useful for modeling mean reversion and forecasting the spread. However, it has a serious drawback because it formally requires both stocks in the candidate pair to have the same long run return, which is unlikely in practice.

The third and final identification strategy, and the one employed in the present study, employs the statistical phenomenon of cointegration (Engle & Granger, 1987) to identify candidate pairs. A formal discussion of this approach is postponed until the next section, but intuitively it is a long-term relationship between nonstationary time series. Cointegration is sometimes colloquially described as a drunk man leading a dog on a leash; while each might wander in a seemingly random pattern, they are connected and cannot drift arbitrarily far apart. If two stock prices are linked in such a way, their prices are likely to revert toward their long-run relationship, yielding profit for a statistical arbitrage strategy. The application of cointegration to pairs trading is discussed extensively in Vidyamurthy (2004).

The theoretical basis for the cointegration approach is rooted in arbitrage pricing theory (APT, Ross, 1976). In particular, Vidyamurthy (2004) argues that the cointegrating relationship is due to a proportional shared risk exposure (whose source is likely unknown and even left unexplored in a purely quantitative implementation). However, Do, Faff, and Hamza (2006) note that this interpretation is somewhat problematic because APT posits the total return to be due to the sum of the risk free rate and the return to risk factor exposure. Thus, pairs trading through cointegration is only heuristically linked to mainstream asset pricing models.

The strategy is often also likened to an application of the Law of one Price. If two stocks are expected to have similar returns (or cash flows) in the future, then their prices should be near each other. Or, in relative terms, if their returns generally follow the same trend, then their price histories should trace similar paths over time.

Among the most widely cited applied work in this area is Gatev, Goetzmann, and Rouwenhorst (2006), who examine daily price data from 1962 to 2002 and yield average annualized excess returns of nearly 11%. They also demonstrate that returns to pairs trading have declined over time, with profits lower in the period after 1989. This finding is reinforced by Chen, Chen, and Li (2012), who suggest that the participation of more arbitrageurs has eroded profitability. To the extent that HFT employ statistical arbitrage strategies, they will eliminate the mispricing and through their competition remove any profits to be made in simple pairs trading algorithms.

The reasonable argument that HFT would destroy pairs trading profitability has not been fully borne out in practice. Like some other pricing anomalies, profitability persists. In one recent study Bowen, Hutchinson, and O'Sullivan (2010) demonstrated that pairs trading remained a profitable strategy during 2007 for the FTSE100 constituent stocks. Perlin (2007) showed profitability in the Brazilian market continued at least through 2006, and Siy-Yap (2009) demonstrated a declining but still profitable implementation in the Canadian market. These examples demonstrate persistence of profitability across a range of trading environments by encompassing the very liquid, high volume environment of the London Stock Exchange and the still developing stock market of Brazil. In any case, the ongoing anomaly suggests the need for further scrutiny of the strategy's profitability in a market characterized by HFT.

2.2 The High Frequency Trading Environment

The effects of HFT on various aspects of markets (including liquidity, trading costs, price efficiency, and correlation) have been widely debated and studied in recent years, sometimes with uncertain or conflicting conclusions. Of particular interest here is the effect of HFT on correlations among equities. Casual empiricism reveals that in recent years correlations among

U.S. equities have increased significantly; this has decreased the effectiveness of stock picking strategies for diversification (e.g., Lauricella & Zuckerman, 2010; Jannarone, 2011). This trend is often attributed to the presence of HFT in the market. The tendency toward generally higher correlations has been formally established in a growing body of literature (Erb, Harvey, & Viskanta, 1994; Longin & Solnik, 1995), and the concept of correlation risk is now prevalent enough that it can be considered a priced risk in portfolio construction (Krishnan, Petkova, & Ritchken, 2009; Buraschi, Porchia, & Trojani, 2010). Of most direct applicability, the link between rising correlations and high frequency trading was explored by Hanson and Muthuswamy (2011).

Higher correlations have two possibly offsetting effects on pairs trading profitability. First, comovement among stocks will likely raise the number of cointegrated pairs to be candidates for pairs trading. Second, higher levels of comovement make it less likely that pairs will diverge to a large enough extent that trading the spread will be profitable. In other words, there will likely be more trading opportunities at smaller profit margins, and one might expect such profits to be taken quickly by high frequency traders.

Faster convergence to efficient market prices would further bolster the position for lower profits from pairs trading. Arguing along those lines, Brogaard, Hendershott, and Riordan (2011) suggest that HFT increases price efficiency by trading in the same direction as permanent price changes but opposite to short term market fluctuations. In a comparison of the Shanghai, Shenzhen, and Hong Kong stock exchanges, Mai and Wang (2011) conclude that more efficient markets lead to lower profits for pairs trading strategies. Similarly, Andrade, di Pietro, and Seasholes (2005) report that pairs trading profits are correlated with uninformed trading. Since HFT is usually implemented by sophisticated investors with an information and speed advantage, higher participation by HFT would be expected to limit pairs trading profitability. These previous studies suggest that within the U.S. market stocks with higher concentration of HFT would be less attractive for statistical arbitrageurs.

By contrast, in a significant theoretical paper, Froot, Scharfstein, and Stein (1992) develop a model in which short-horizon traders cause markets to become less efficient. Furthermore, HFT can be motivated not by firm fundamentals but rather trade flow, a phenomenon sometimes termed flow toxicity (Arnuk & Saluzzi, 2008; Easley, Prado, & O'Hara, 2012). To the extent that toxic order flow is present in markets, prices can reflect the popularity of a given strategy, macroeconomic news, or even investment sentiment and rumor. This might cause increased volatility and more mispricing opportunities due to temporary overreactions from HFT. Such an outcome would imply more profitable opportunities among stocks with greater levels of HFT volume.

Given the division in the literature and past results, the data and testing in the remainder of this paper is exploratory in nature, seeking to answer two questions. One, does the previously observed trend toward lower profitability from a pairs trading strategy continue with more recent market data? Two, is there a difference in this effect due to high frequency trading volume?

3.0 Data and Method

The sample for this study is comprised of all common stocks (CRSP share codes 10 and 11) that trade above $1 and are included in both the CRSP and Thomson Reuters Institutional Holdings databases from 1985 to 2011. In additional screening, stocks that have one or more days with zero volume are eliminated from the sample. This ensures a minimal level of liquidity in the candidate stocks. The total sample includes 371,416 firm-quarter observations, which is split, as explained below, into a training period from 1985 to 1994 (118,060 firm-quarters) and a trading period from 1995 to 2010 (253,356 firm-quarters).

One necessary data correction involves the Thomson Reuters data on net changes in shares held by institutions. As Zhang (2010) notes, from the second quarter of 2006 through the first quarter of 2007 the net changes are incorrectly reported as the previous quarter's stock holdings multiplied by negative one. Therefore, we manually recalculate the net change data for these quarters by taking the difference in share reported holdings in adjacent quarters.

3.1 Estimating HFT volume

Market data do not allow for direct observation of HFT volume. This complication has spawned a number of proxies and differing methodologies within the industry and among researchers. Proprietary research, such as that conducted by the TABB Group, generally attempt to identify trading activity by firms that operate primarily with HFT strategies (e.g., Getco and Citadel). A form of this direct identification is now available for academic research through the NASDAQ, which supplies data under a non-disclosure agreement. These data have been utilized, for example, by Brogaard, Hendershott, and Riordan (2011) in their examination of HFT's effect on price discovery.

The NASDAQ data remain problematic, however, for several reasons. First, the information is drawn from a stratified sample of just 120 stocks. Second, the identification of HFT is done by NASDAQ, which impairs replicability and transparency. Third, it fails to provide an out-of-sample model that can be used to estimate HFT across a broader time span. Therefore, while the NASDAQ data provide an intriguing opportunity for study, they are applicable in all situations. In particular, the present study requires a technique to calculate approximate HFT activity over a nearly twenty year span of time and for a broad range of equities.

Zhang (2010) proposes one such method for estimating HFT volume through the use of data available from CRSP and the Thomson Reuters Institutional Holdings databases. The measure is built on a turnover-based identity, in which total trading volume is subdivided into three classifications, based on the participants involved: individual investors, institutional investors, and high frequency traders. Further refinements lead to observable variables in the following equation:

$$TO = INSTTO*INST + INDIVTO*INDIV + HFT$$

in which TO is total stock turnover, INSTTO is institutional turnover, INDIVTO is individual turnover, INST and INDIV are (respectively) institutional holdings and individual holdings as a fraction of total shares outstanding. Three of these variables, namely TO, INST, and INSTTO, are observable from the CRSP and Thomson Reuters databases. Figure 1 displays these series over the entire sample period. Most noticeable is the strong uptick in market turnover (TO) that begins in the mid-1990s but abates somewhat following the credit crisis of 2008.

Three further assumptions are necessary to facilitate an estimate of HFT. First, it is assumed that no high frequency trading existed prior to the beginning of 1995. This choice of date by Zhang (2010) is apparently ad hoc, due to visual examination of turnover data. Pinpointing the beginning of HFT is impossible because it represents a gradual, evolutionary change in the market. Its origins can be traced at least as far back as the SOES “bandits” of the late 1980s (Patterson, 2012), and HFT was certainly in force by the time of price decimalization in 2000. Using piecewise linear regression to search for a single breakpoint that minimizes the sum of squared errors for the turnover data suggests the beginning of 1993 as the date when HFT began to increase market turnover.

The truly relevant question is how much the choice of sample period influences average measures of the market during the estimation period. Table 1 displays value-weighted averages[2] of institutional holdings, institutional turnover, and total market turnover for various sample periods. The sample always begins in 1985 and the ending year varies from 1992 through 1999. Throughout this period, the averages are quite stable, suggesting that the HFT measurement is robust to the precise specification of the estimation period. Therefore, while acknowledging the multiplicity of possible dates, we choose to follow Zhang (2010) and use the start of 1995 as the date when HFT began in earnest.

The second assumption is that HFT do not hold positions at the end of any quarter. This strong assumption is justified by the short holding periods of HFT strategies and the general goal of carrying no overnight inventory. It implies that INDIV + INST = 1 at all times when examining market closing data.

Third, Zhang (2010) assumes that the trading behavior of individuals relative to institutions remains stable over time. He is quick to point out that this does not require stable patterns of behavior, but rather a stable ratio. Individuals and institutions will tend to trade more or fewer shares in tandem with one another so that the ratio of their turnover is stable.

In calculating total market turnover, an adjustment is necessary for the potential double-counting of dealer trades of NASDAQ stocks (Gould & Kleidon, 1994). The over-reporting of volume on the NASDAQ was examined by Atkins and Dyl (1997), who documented an approximate 50 percent drop in volume for the stock of firms switching from NASDAQ to

[2] Value-weighted averages are calculated throughout this paper by using average market capitalization for each firm-quarter observation. We believe that one source of slight discrepancies between our calculations and Zhang's could be due to different weighting schemes.

NYSE. For this reason, Zhang (2010) suggests using half of the reported volume for NASDAQ stocks.

There is some evidence, however, that the problem of inflated volume for NASDAQ stocks has diminished in recent years. Anderson and Dyl (2005) find that the decrease in volume has declined to 38% over the five-year period ending in 2002. They suggest a number of structural changes in the market that could combine to cause this change, including the growth of ECNs, competition from public limit orders, and rule changes put in place for reporting of trades to the NASDAQ. Furthermore, they note that firms with high daily volume on average experience a greater rate of over-counting and suggest that a separate adjustment factor be used for high- and low-volume stocks. By following Zhang (2010) and dividing NASDAQ volume by two, it is plausible that the present investigation understates total market turnover in the more recent years of the sample period. Due to this, the calculated HFT volume is also likely understated.

The procedures outlined above allow for an estimation of the ratio of individual turnover to institutional turnover (INSDIVTO/INSTTO). Zhang (2010) estimates this ratio to be 71.81%, while our sample yields an estimate of 82%. The differential could arise due to different samples and different weighting criteria, and the results here suggest lower levels of HFT volume in the market: 71% of volume in the U.S. market in 2009, compared to Zhang's (2010) estimate of 78% and the TABB Group's estimate of 73%.

The actual level of HFT volume for the various stocks is not used directly in any further calculations in this study. Instead, the stocks are ranked by this measure and split into vigintiles for use examination of pairs trading profitability. Since the rankings will be robust to the particular estimate, we retain our figure of 82% and calculate HFT using the following equation:

*HFT = TO – INSTTO*INST – (0.82*INSTTO)*(1 – INST)*

This variable is calculated for each firm-quarter observation in the sample, and stocks are ranked within each quarter and split into vigintiles portfolios for further testing.

3.2 Cointegration testing

Cointegration can be conceptually described as a long-run equilibrium relationship between two (or more) nonstationary time series. Independently, two nonstationary time series will wander unpredictably, but there exists a linear combination of those same variables that is stationary. Figure 2 provides an example of two stocks that are cointegrated. Their price history follows common trends, and the two price series appear to revert toward parity whenever they drift apart. This is reinforced in Figure 3, which plots the spread between the two stocks. The spread is a stationary process, with multiple crossings of its (near zero) mean value. This reversion property of the spread is what creates a profitable trading opportunity, as outlined in this and the next section.

Granger (1981) formally introduced cointegration and coined the term, while the first formal test for cointegration was presented by Engle and Granger (1987). In the context of financial time series, their two-step approach begins by regressing the log price of stock A on the log price of stock B, which implies the following relationship:

$$\log(p_t^A) - \gamma \log(p_t^B) = \mu + \varepsilon_t,$$

with γ called the cointegrating coefficient and the constant term μ the premium of stock A versus B. This regression has been termed superconsistent because the estimate $\hat{\beta}$ converges to its true value at a rate of T, rather than the usual convergence rate of $T^{1/2}$ (Stock, 1987).

Due to market efficiency, it is assumed that the log price series are random walks and hence nonstationary. If the two series are cointegrated, however, the appropriately constructed linear combination of prices will be stationary. Hence, the second step in the test for cointegration can be conducted by using the augmented Dickey-Fuller (ADF) test for the stationarity of the residuals. The critical values for the test have previously been generated through Monte Carlo simulation. The test used in this study utilizes the implementation in the R statistical environment, which draws its critical values from Banerjee, Dolado, Galbraith, & Hendry (1993).

Once two stocks have been deemed to be cointegrated during the testing period, the spread can be considered a synthetic trading instrument, using the following calculation for a subsequent out-of-sample period:

$$spread_t = \log(p_t^A) - \hat{\gamma}\log(p_t^B) - \hat{\mu}$$

Because the spread is a stationary time series, it is assumed that the mean and standard deviation from the testing period will be constant through the out-of-sample trading period as well. If the spread moves significantly away from its long-run mean, a trader can take positions that will profit from reversion. The next section outlines the details of such a trading strategy, as employed in this study.

3.3 Trading Strategy

Recall that the primary goal of our research is to understand the effect of HFT on the profitability of pairs trading. Since the focus of the work is on comparing profits across different trading regimes (over both time and HFT volume), the realism of our trading strategy is not of primary concern. It is not the absolute level of profit that is of interest, but rather its trend. Therefore, we follow a rather basic trading strategy that follows a structure similar to that of Gatev, Goetzmann, and Rouwenhorst (2006) and later updated by Do and Faff (2010).

Statistical arbitrage strategies based on cointegration all follow the same basic three part format. First, an initial universe of candidate stocks is identified. This preliminary step allows a trading scheme focused on a particular industry or other subset that might be presumed to have a high degree of comovement in stock returns. Second, the candidate pairs are tested for cointegration using the chosen statistical test, and the spread is calculated from those results. Third, when the spread widens beyond some predefined threshold, the trader takes the appropriate long and short positions to profit from reversion to the long run relationship.

The implementation employed here follows a two-stage structure. The first stage (training period) consists of one year of daily price observations for a broad universe of candidate stocks: all stocks priced over one dollar and with at least one reported trade each day. These stocks are sorted into vigintiles based on HFT volume, as calculated from Zhang's (2010) methodology. Each vigintile contains between 353 (in 2010) and 501 (in 1997) different stocks. The one-year training periods coincide with the calendar year and are non-overlapping, yielding 16 distinct trading periods for comparison. (Note that the subsequent trading period does overlap with another training period.)

Within each vigintile, all possible pairs are tested for cointegration using the Engle-Granger two-step procedure. By testing all possible pairs, this process does not consider other variables that are sometimes included in cointegration analysis, namely a desire for market neutrality (for example, β spread less than 0.2) or a consideration of matching stocks based on industry, size, book-to-market, or any other characteristic (some of these are utilized by Velayutham, Lukman, Chiu, & Modarresi [2010]). By running the cointegration test across all stocks within the HFT vigintile, this study identifies the largest universe of cointegrated stocks. At the same time, it can increase the risk of trading any particular pair. The desire to emphasize the influence of HFT motivated the omission of further screening variables. Therefore, any pairs whose residuals are determined stationary by the ADF test at a 10% level of significance are considered trading candidates in the stage two of the trading algorithm.

In the second stage, the regression coefficients from the Engle-Granger test are used to construct the spread for all cointegrated pairs on an out-of-sample trading period of 125 days. The spread is then treated as a synthetic investment vehicle, with a trader taking the appropriate long and short positions to profit from a rise or fall in the spread. The mechanical trading rule employed here is to enter a trade whenever the spread moves more than two standard deviations away from its mean (with the mean and standard deviation calculated from the training period and considered constant over the entire trading period). The trade is exited at a profit if the spread reverts and crosses its mean value. The trade is exited at a loss if the spread widens to more than three standard deviations from the mean. Finally, all pairs are closed at the end of the 125-day trading period, regardless of the profit or loss incurred.

Figure 4 depicts one example of the trading process for a cointegrated pair. The time period displayed is of the trading period only (125 days). The top panel shows the spread, which in this case spends most of the trading period below its mean value from the training period. The dotted lines represent levels two and three standard deviations below the mean (respectively, the entry and stop loss signals). The middle panel is a depiction of the trading signal, which takes a zero value when there is no position and a one otherwise. Finally, the bottom graph portrays the cumulative profit from the investment rule. In this particular example, there are three times that the trade is entered. The first ends in a loss when the spread moves below the third standard deviation, while the second and third periods end in a profit when the spread moves below the two-standard deviation line and reverts to the mean. Overall, this is a profitable pairs trade.

Log returns from the trading strategy are calculated as the cumulative sum of the difference of the spread. This carries the implicit assumption that cash flows neither earn nor incur any interest costs. Furthermore, there is no consideration of capital not invested in the strategy. Instead, the portfolio return is based on equal investments in all available pairs whenever the trading criteria are met. Again, this is a very basic trading strategy, and the level of profits is not of direct interest. Rather, the results in the next section are focused on the differences in profitability over time and across vigintiles of HFT volume.

4.0 Results

Table 2 (Panels A and B) presents results on the percentage of pairs within each vigintile that are identified as cointegrated using the Engle-Granger two-step procedure and a 10% significance level in the ADF test of the residuals. Two trends are readily evident from the results. First, a higher percentage of candidate pairs are identified as cointegrated in more recent years. For example, in the vigintile with the greatest HFT volume, cointegrated pairs increase from 18.4% in 1995 to 32.7% in 2010. Though the effect is certainly not monotonic, it is the general trend across all vigintiles. This suggests that the trend toward higher comovement in the market dominates. This creates more trading signals for further scrutiny in the trading scheme.

The second general trend is that stocks with higher levels of HFT also have a greater percentage of cointegrated pairs within a given year. For instance, in 2010, the vigintile with the lowest HFT volume had only 9.0% of its pairs cointegrated, while the highest vigintile had 32.7% of pairs identified as cointegrated. Stocks with higher levels of HFT are more likely to have similar return series and be cointegrated.

The stocks identified as cointegrated are then examined for their trading signals and profits or losses, using the trading strategy outlined above. Results appear in Table 3. At least three observations can be made about these results. First, stocks in higher vigintiles of HFT activity have higher profitability, on average. Figure 5 depicts results for the year 2009. It is representative in that profitability does not increase monotonically with higher levels of HFT, but the profitability tends to be greater in the top ten vigintiles than in the lower ten. This provides preliminary evidence that stocks with more HFT activity provide greater opportunities for profits from statistical arbitrage strategies.

Second, the range of profitability is larger in more recent years. Of course, the range of HFT volume has also increased over the same time period. The coincident timing of these two changes in market structure further suggests an influence of HFT on pairs trading profitability.

Third, these two trends combine to explain some earlier results of a shift toward lower profitability for pairs trading, as in Gatev, Goetzmann, and Rouwenhorst (2006). If a trading strategy does not consider the effect of HFT, it can result in a mix of profitable and unprofitable positions that cancel each other out, creating the illusion of decreased profitability overall. Instead of pairs trading losing its viability as a general strategy, it has become more necessary to screen the universe of stocks appropriately to focus on pairs most likely to be profitable.

5.0 Conclusion

The results presented here can help formulate an answer to the research questions under consideration. Higher levels of comovement among U.S. equities has increased the number of cointegrated stock price series. This shift creates additional trading opportunities for statistical arbitrage.

Profitability of those statistical arbitrage opportunities remains steady in the highest HFT volume vigintile, but declines markedly in vigintiles with lower levels of HFT. This is an indication that stocks with more HFT activity are more volatile, with the spread widening and reverting often enough to provide profit for appropriate positions to trade the synthetic trading instrument based on the spread. This study thus contributes to the literature on HFT, in addition to an understanding of pairs trading in modern markets.

In extensions of the current work, we intend to analyze returns in excess of other risk factors, including the Fama-French three factor model. Portfolios will also be split by market capitalization to ensure that HFT is distinct from size as an influence on pairs trading profitability. The preliminary results presented here demonstrate that further research and refinement is likely to be fruitful.

One limitation of this study is the use of daily closing prices. To the extent that HFT employs statistical arbitrage strategies, they likely enter and exit positions at a much faster pace than would be captured in the data. We are currently working on an extension of the testing presented here on a high frequency data sample. However, we contend that daily data remain important in revealing the overall market trend. Furthermore, daily prices allow comparison over a long time horizon, more so than will be possible with higher frequency data. Additionally, the HFT proxy employed is based on firm-quarter observations, so further refinement below daily pricing begins to raise questions about the time-scale discrepancies among the variables. Finally, the use of daily data allows direct comparison to previous literature.

Results here apply to the U.S. stock market and could likely be replicated in other developed markets around the world. An interesting extension of the work would be to examine markets with different volumes of HFT, levels of development, and microstructural characteristics. Also, statistical arbitrage is not limited to pairs trading, nor is it limited to the equity market. The strategy can be implemented in index tracking, basket portfolios, and derivatives markets. We leave it for future research to consider the effect, if any, of HFT in those settings.

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Table 1. Value-weighted averages of INST, INSTTO, and TO for various sample periods

Sample period	INST	INSTTO	TO
1985 - 1992	0.4887	0.1854	0.1684
1985 - 1993	0.4932	0.1858	0.1690
1985 - 1994	0.4981	0.1859	0.1695
1985 - 1995	0.5033	0.1868	0.1725
1985 - 1996	0.5082	0.1877	0.1755
1985 - 1997	0.5138	0.1874	0.1793
1985 - 1998	0.5181	0.1869	0.1825
1985 - 1999	0.5220	0.1883	0.1871

Table 2 (Panel A). Percent of candidate pairs that are cointegrated

	Lowest	2	3	4	5	6	7	8	9	10
1995	1.0	5.9	7.1	13.0	9.6	10.4	10.1	10.6	8.8	9.1
1996	0.2	4.3	3.8	6.9	6.8	8.8	8.7	10.6	12.6	7.2
1997	0.8	3.1	9.4	4.6	10.7	9.0	7.4	9.5	7.5	7.6
1998	1.2	6.7	7.7	10.3	12.3	8.5	12.4	12.4	8.7	10.7
1999	1.2	2.1	7.9	8.0	5.1	7.7	7.7	7.1	3.4	5.8
2000	1.2	6.2	9.8	12.8	9.5	14.0	12.2	11.1	8.6	10.9
2001	1.3	5.2	7.7	9.7	14.4	6.7	20.2	9.2	9.7	8.1
2002	0.7	9.8	9.9	14.6	11.2	13.6	8.4	10.6	7.9	7.2
2003	3.2	10.8	11.4	14.5	15.7	9.7	8.5	8.5	6.5	9.8
2004	1.0	8.4	14.0	17.5	21.5	24.5	15.0	15.5	10.2	15.4
2005	2.3	13.9	8.1	15.1	12.8	14.4	13.1	11.6	6.9	12.1
2006	2.4	14.8	15.0	14.8	23.2	11.3	13.8	13.3	8.1	19.7
2007	7.2	4.9	6.8	6.2	5.6	5.9	6.2	14.3	11.3	13.7
2008	2.7	2.3	3.9	1.7	3.4	1.8	1.5	8.9	8.0	11.6
2009	4.4	6.3	3.9	8.3	3.9	2.9	4.8	12.3	24.2	29.8
2010	2.4	9.0	6.8	14.3	7.7	7.2	5.5	9.8	11.1	11.5

The table above gives the percent of candidate pairs for each HFT vigintile that are identified as cointegrated using the Engle-Granger two-step procedure. Vigintile one contains the lowest levels of HFT.

Table 2 (Panel B). Percent of candidate pairs that are cointegrated

	11	12	13	14	15	16	17	18	19	Highest
1995	9.3	4.6	9.2	6.9	4.7	4.5	10.6	11.0	16.8	18.4
1996	10.0	9.7	10.0	9.2	13.7	11.9	15.1	10.3	13.5	20.0
1997	4.4	4.6	6.3	6.5	7.8	7.4	6.2	5.3	10.2	12.5
1998	8.9	8.8	8.2	15.2	6.4	8.3	11.8	12.3	12.8	13.8
1999	7.5	6.3	7.5	12.7	17.1	11.9	8.2	14.1	14.4	14.7
2000	8.7	16.6	17.4	19.6	25.8	21.1	12.0	16.5	7.1	12.1
2001	8.6	8.7	11.8	19.4	18.5	16.5	26.9	16.0	20.0	16.7
2002	6.8	9.8	17.8	24.5	20.2	25.3	29.9	26.3	20.7	27.8
2003	14.0	15.7	21.8	30.4	41.5	31.3	47.9	44.5	54.6	56.5
2004	27.7	38.8	40.6	46.3	34.8	47.6	43.3	31.9	34.8	33.1
2005	14.9	21.6	34.0	27.2	30.8	40.5	27.2	23.3	34.2	32.4
2006	25.1	25.9	31.2	33.8	28.4	35.1	23.8	38.4	13.7	23.6
2007	11.6	27.7	18.9	13.4	18.1	17.8	14.9	18.9	11.5	8.6
2008	20.5	20.7	39.0	26.6	31.9	20.3	23.9	16.6	20.1	20.4
2009	33.8	39.7	48.7	43.8	42.2	49.2	49.5	43.7	56.5	53.1
2010	18.7	13.4	17.5	23.9	25.4	21.4	25.1	24.1	20.5	32.7

The table above gives the percent of candidate pairs for each HFT vigintile that are identified as cointegrated using the Engle-Granger two-step procedure. Vigintile twenty contains the highest levels of HFT.

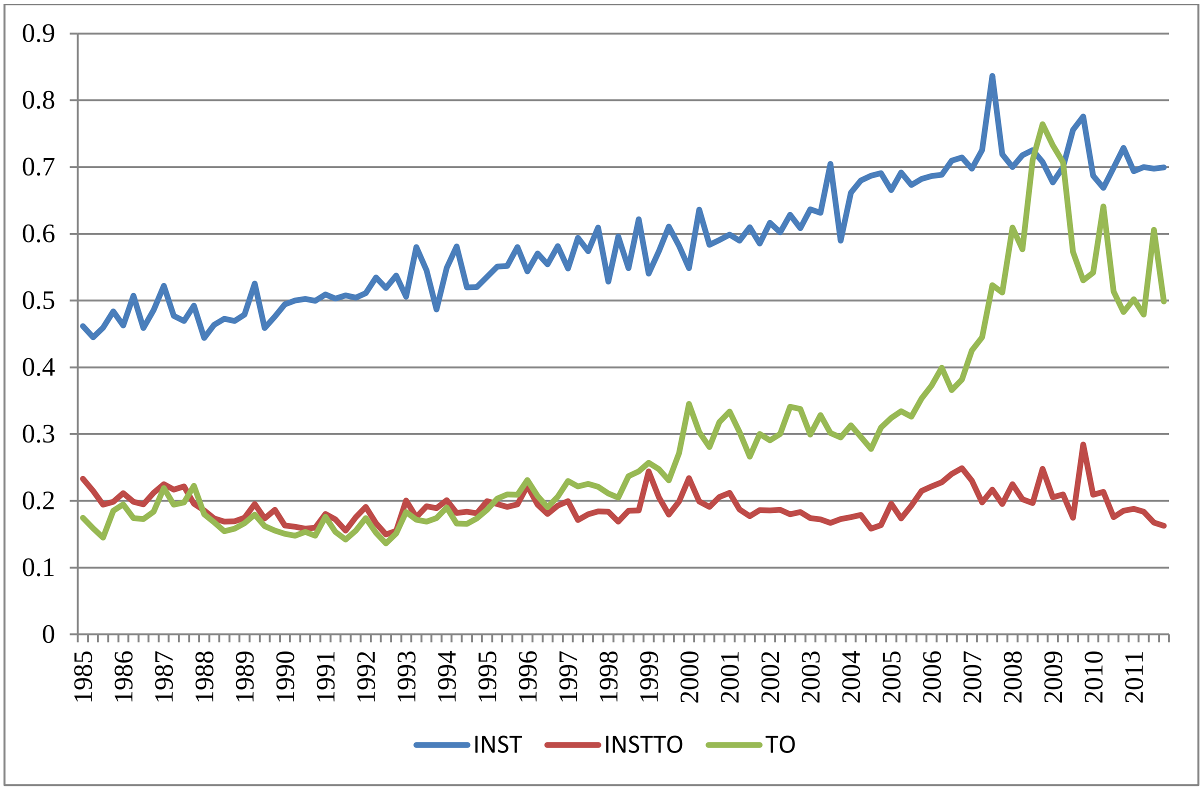
Table 3 (Panel A). Profitability from pairs trading strategy

	Lowest	2	3	4	5	6	7	8	9	10
1995	-0.75	5.18	4.33	3.81	-0.24	3.77	5.82	5.03	4.47	2.47
1996	0.58	7.39	4.67	-1.28	12.46	-2.63	6.28	-1.78	10.14	8.73
1997	0.35	5.38	-3.01	9.21	9.85	-0.37	11.55	16.57	6.79	14.78
1998	-1.83	6.12	-7.24	-8.16	6.80	18.05	13.11	17.91	13.17	23.08
1999	-1.83	-1.21	-7.24	-6.93	4.77	-12.81	11.26	-4.63	-9.51	-3.41
2000	-2.65	21.07	8.45	-1.18	14.17	-24.19	-2.93	-16.51	26.99	10.16
2001	1.91	4.77	0.96	-6.03	1.78	1.65	8.03	-1.97	3.74	14.13
2002	0.31	8.31	17.31	-3.26	13.62	7.15	5.87	-5.60	7.53	3.94
2003	-5.44	15.62	-3.53	4.68	4.76	7.94	12.16	12.16	-1.23	3.78
2004	0.60	-15.55	3.73	5.72	25.30	4.30	-6.39	-7.79	-2.99	-1.11
2005	-0.69	2.10	-5.24	-5.69	3.41	16.72	15.61	1.87	-3.44	4.00
2006	-0.26	1.48	3.19	-8.18	-17.23	11.05	-4.15	-6.68	-6.73	9.15
2007	1.71	1.78	7.01	2.41	-6.33	1.34	-4.40	-3.29	-0.06	-6.88
2008	20.05	-2.22	17.43	1.37	3.15	7.49	2.25	12.78	20.01	5.73
2009	6.66	-0.71	1.83	0.13	0.50	-0.36	7.90	5.80	16.96	34.68
2010	1.22	-5.54	-1.62	-6.00	-2.19	-5.38	-2.76	2.48	-12.60	-11.45

Table 3 (Panel B). Profitability from pairs trading strategy

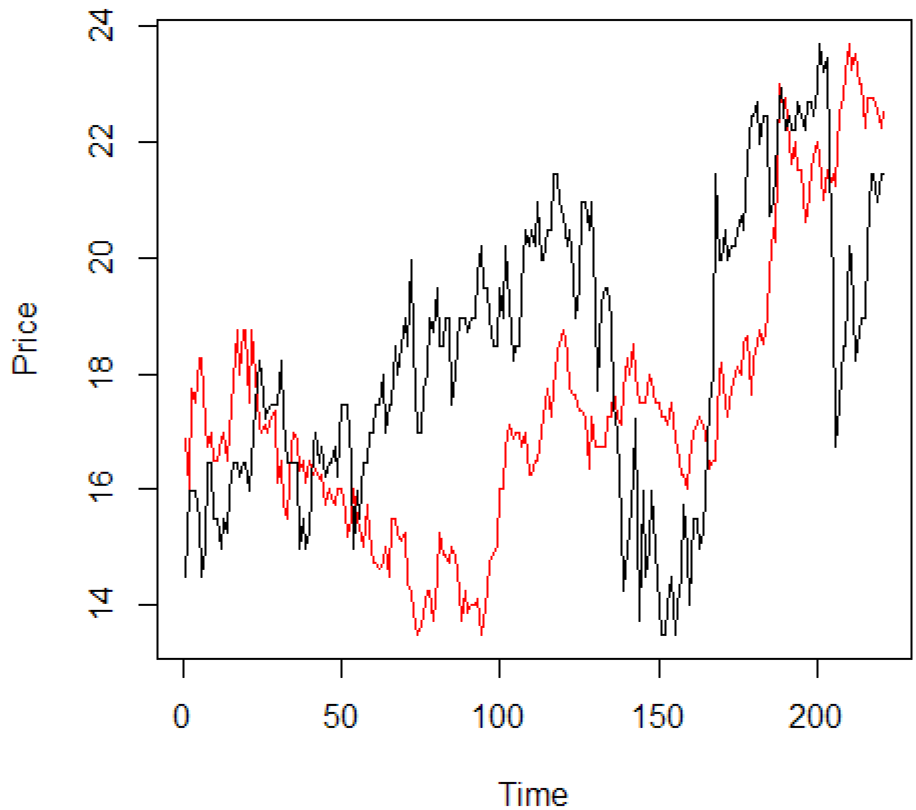
	11	12	13	14	15	16	17	18	19	Highest
1995	-5.93	1.54	4.27	1.77	6.92	1.09	10.82	22.89	26.38	12.23
1996	18.42	18.10	2.64	1.78	19.92	10.20	34.08	22.89	23.26	12.23
1997	4.81	4.95	2.47	-8.34	8.20	9.80	15.28	-1.52	20.40	18.24
1998	-4.73	19.54	15.71	43.24	15.58	19.76	33.56	21.24	-23.74	58.24
1999	19.44	-5.87	17.63	-16.72	60.62	-9.69	-33.83	38.15	5.96	7.57
2000	-3.02	-12.50	16.63	11.33	7.94	26.75	7.23	31.99	-2.57	13.98
2001	14.46	7.24	-7.88	7.68	-0.49	-9.74	35.21	11.20	42.82	2.84
2002	12.26	14.31	-0.53	14.60	18.92	34.33	25.09	39.31	65.31	42.35
2003	11.32	9.22	3.94	26.39	22.34	27.28	-22.68	24.07	47.28	29.01
2004	-18.45	24.81	-25.89	21.38	10.34	60.63	22.52	12.83	-13.22	15.19
2005	5.44	10.56	9.66	15.17	32.63	-3.40	8.36	8.21	44.60	-16.13
2006	-3.79	-0.23	-6.81	14.19	-4.82	7.89	-15.29	-4.83	2.85	4.22
2007	3.72	7.94	-13.33	11.29	-7.45	14.14	3.98	7.60	3.88	-10.77
2008	15.14	42.50	13.92	24.98	64.75	13.62	20.09	40.17	29.99	31.89
2009	44.45	16.61	65.39	36.95	67.20	30.17	43.03	33.22	0.47	28.66
2010	-13.70	-2.21	11.88	-5.82	-2.53	-6.95	-14.75	2.25	1.72	5.87

Figure 1. Time series of institutional ownership (INST), institutional turnover (INSTTO) and market turnover (TO)



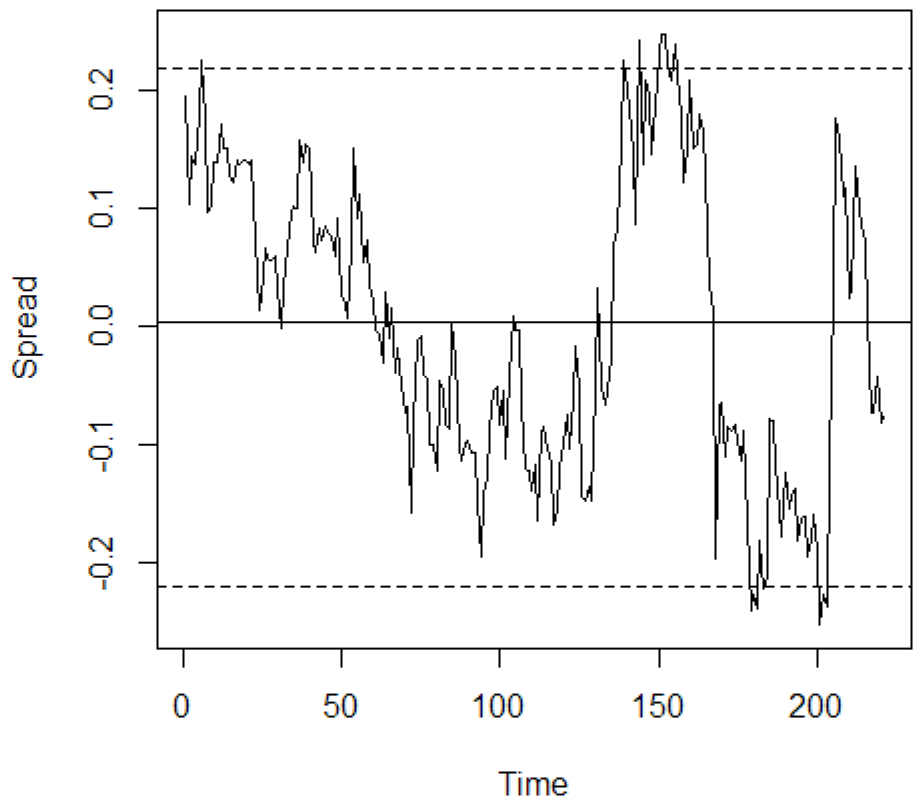
This graph displays the variables INST, INSTTO, and TO over the sample period from 1985 through 2011. The series are value-weighted averages over all firms with prices above $1 that are included in CRSP and Thomson Reuters data.

Figure 2. Example of the price history of two cointegrated stocks.



This graph displays one year of daily price history for two stocks that are cointegrated.

Figure 3. Spread between two cointegrated stocks



The time series is the spread between the two stocks displayed in Figure 2. The three horizontal lines represent the mean of the price series (solid line near zero) and a distance two standard deviations above and below the mean (dashed lines).

Figure 4. An example of a cointegrated pair, its trading signal, and cumulative profitability.

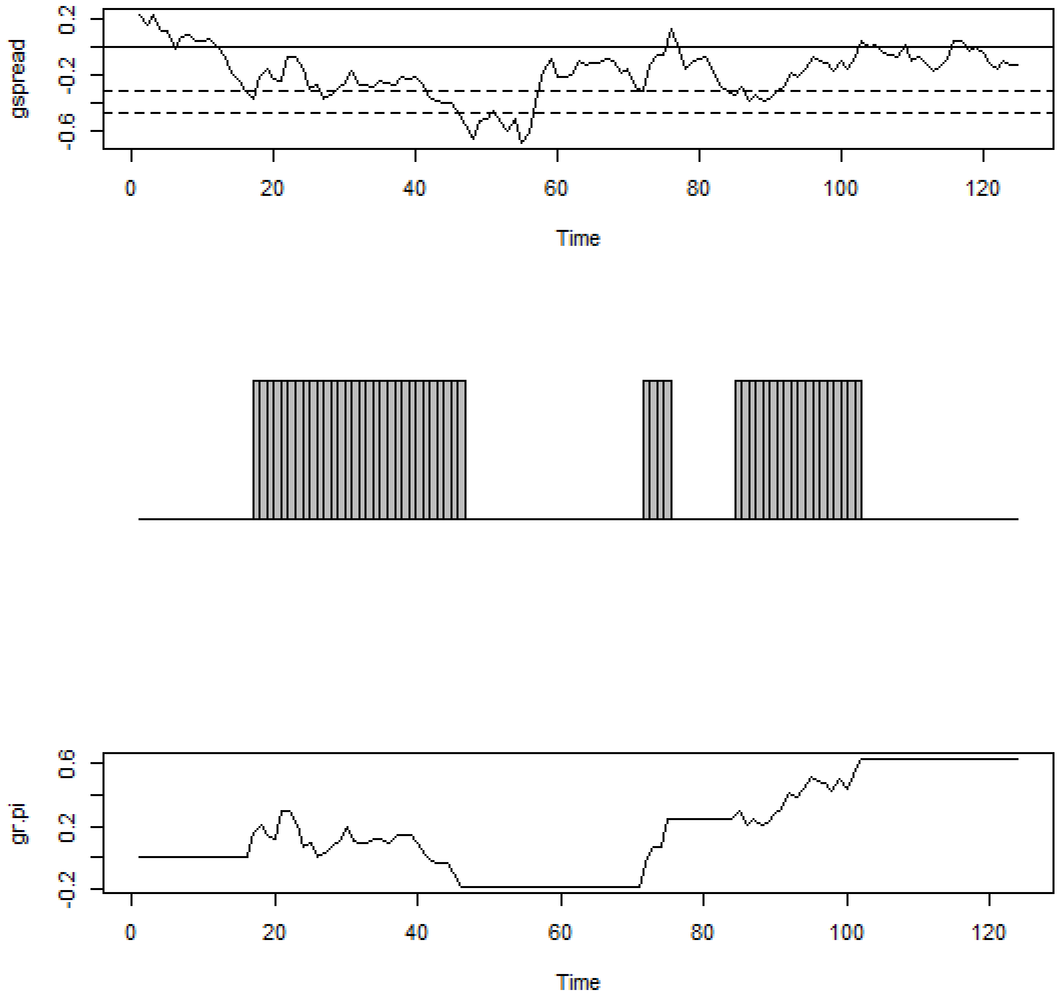
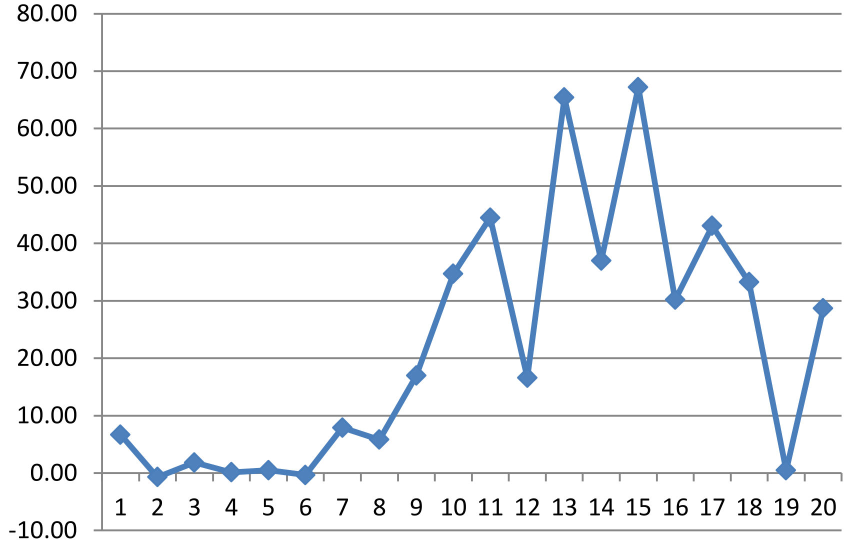


Figure 5. Profitability of the pairs trading strategy, 2009



The graph depicts profitability for the trading strategy in 2009. The horizontal axis is HFT vigintile, with one being the lowest amount of HFT and twenty the highest. The vertical axis is profitability.