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Statistical pairs trading and analyst recommendations

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Abstract
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STATISTICAL PAIRS TRADING AND ANALYST RECOMMENDATIONS

PURPOSE OF THE STUDY

Previous literature has documented statistical pairs trading with stocks yielding positive abnormal returns. This phenomenon violates the weak form of the efficient market hypothesis and cannot be explained by known risk factors. An emerging field in pairs trading studies focused on information flow has provided interesting results on the relation of statistical trading and information events, but without being able to explain the abnormal returns. This thesis aims to elaborate this relation by studying analyst recommendations which have been shown to be related to both stock price movements and information events, but have not been previously studied in connection to statistical pairs trading.

DATA

I study a daily return data of all U.S. utility sector stocks listed on the NYSE, AMEX and NASDAQ exchanges during years 2000 to 2010. Of this sample I form 20 stock pairs every 6 months for statistical pairs trading. I match the 20 pairs with newly issued analyst recommendations during trading. The full data consists of approximately 150 stocks forming on average 6 602 potential pairs every 6 months, and 3 126 matched analyst recommendations.

RESULTS

My results support previous findings that statistical pairs trading yields positive abnormal returns, though smaller in recent years, and that relative analyst recommendations hold valuable information to investors. However, I find that stock prices do not evidence post-recommendations drift in pairs after being issued divergent recommendations.

Divergent recommendations are a signal of a statistical stock pair breaking up. The spread may move to the direction recommendations indicate or irrationally to the opposite direction and hence the direction of the spread between a pair cannot be inferred from recommendations. Pairs breaking up causes negative return to pairs trading and thus the aggregate abnormal positive return to pairs trading is driven by pairs that are not issued divergent recommendations.

KEYWORDS

Pairs trading, analyst recommendations, post-recommendation stock price drift

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TILASTOLLINEN KAUPANKÄYNTI OSAKEPAREILLA JA ANALYYTIKOIDEN SUOSITUKSET

TUTKIELMAN TAVOITTEET

Aiemmat tutkimukset ovat osoittaneet tilastollisen kaupankäynnin osakepareilla tuottavan positiivisia ylituottoja. Ilmiö rikkoo tehokkaiden markkinoiden hypoteesin heikkoa muotoa eikä sitä ole kyetty selittämään tunnetuilla riskitekijöillä. Tutkimus informaation vaikutuksista osakepareilla käytävään tilastolliseen kaupankäyntiin on tarjonnut mielenkiintoisia tuloksia tilastollisen kaupankäynnin ja uuden informaation suhteesta pystymättä kuitenkaan selittämään tilastollisen kaupankäynnin ylituottoja. Tämä tutkimus pyrkii laajentamaan tietämystämme tästä suhteesta tarkastelemalla analyytikoiden osakesuosituksia, joiden on havaittu olevan yhteydessä sekä osakekursseihin että uuteen markkinainformaatioon, mutta joita ei ole aiemmin tutkittu yhteydessä tilastolliseen kaupankäyntiin osakepareilla.

LÄHDEAINEISTO

Tutkin ilmiötä päivittäisellä tuottoaineistolla Yhdysvaltalaisista yhteiskuntahyödykkeet-toimialan listatuista osakkeista vuosina 2000–2010. Muodostan aineistosta 20 osakeparia puolivuosittain, joilla käyn tilastollisesti kauppaa. Näihin 20 pariin yhdistän kaupankäynnin aikana annetut analyytikkosuositukset. Lopullinen aineisto käsittää noin 150 osaketta muodostaen keskimäärin 6 602 mahdollista puolivuosittain testattua osakeparia, ja yhteensä 3 126 analyytikkosuositusta näille pareille.

TULOKSET

Tulokseni tukevat aiempia tutkimuksia: tilastollinen kaupankäynti osakepareilla tuottaa positiivisia ylituottoja ja analyytikoiden suhteelliset osakesuositukset sisältävät arvokasta tietoa sijoittajille. Osakeparin kurssimuutokset eivät kuitenkaan seuraa analyytikkosuosituksia, kun suositukset osakkeille ovat eriäviä.

Eriävät suositukset ovat signaali osakeparin hajoamisesta. Parit voivat erkaantua suositusten osoittamaan suuntaan tai irrationaalisesti vastakkaiseen suuntaan, joten hajoamisen suuntaa ei voi päätellä suositusten suunnasta. Hajoavat parit aiheuttavat negatiivisia tuottoja ja positiiviset ylituotot osakepareilla käytävälle tilastolliselle kaupankäynnille aiheutuvat pareista, joille analyytikot eivät anna eriäviä suosituksia.

AVAINSANAT

Osakepari, tilastollinen kaupankäynti, analyytikkosuositukset

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1. Introduction

Pairs trading as a statistical arbitrage trading strategy is a market neutral strategy commonly used by hedge fund managers and investment banks' proprietary trading desks. An extensive group of hedge funds defines pairs trading as one of their investment strategies, which argues the fact that believers in abnormal profits through pairs trading are numerous. Indeed, for a hedge fund manager pairs trading provides many desired qualities: market neutrality, leverage and indifference about absolute pricing.

Pairs trading is a trading strategy where a pair is formed of two assets to which a relationship can be estimated. As the asset prices deviate from the estimated relationship the relative loser is bought and the relative winner sold short in anticipation that the assets will converge back to the estimated relationship. When the assets converge the positions are closed and trader makes a profit amounting to the spread that converged between the assets.

The popularity among practitioners has woken an academic research studying pairs trading. Most of the research is focused on the profitability of different strategies in different settings and trying to unfold the optimal implementation of pairs trading. One of the most studied is a simple statistical pairs trading strategy that Gatev, Goetzmann and Rouwenhorst (1999, 2006) have shown to generate excess return of up to 11% per annum by trading stock pairs. Strategy that generates abnormal return by exploiting solely information in past stock prices violates the weak form of the efficient market hypothesis. Since the publication of the first article by Gatev et al. in 1999 scholars have tested the simple strategy without yet to find the excess return being related to any known risk factors or other possible explanatory variables. Furthermore, several studies with recent data have found the strategy still returning abnormal profits.

In addition to statistical arbitrage another branch within pairs trading is fundamental pricing. The field is based on the Law of One Price principles that assets with similar payoffs should be priced equally, and payoffs can be determined through fundamental information. Stock analysts are a large group in the profession of analyzing fundamental company data. Their recommendations can be interpreted as estimates of future payoffs. An individual analyst giving recommendations to several securities is relatively ranking the expected performance of those securities. Furthermore, as analysts often monitor similar companies, their recommendations have an even deeper relative aspect. Yu (2011) tests this aspect and finds that pairs trading on individual analysts' divergent recommendations yields abnormal positive return of up to 2.2% in 6 months. Yu (2011) defines divergent recommendations as two differing recommendations that are given to two stocks *by the same analyst on the same date*, e.g. Wall Street Journal's all-star analyst Neil Kalton from Wells Fargo issuing a hold recommendation to Westar Energy and a strong buy to Scana Corporation on the 18th September 2009.

Studies by Gatev et al. (2006) and Yu (2011) share a number of interesting qualities in respect to sample stocks, trading, excess return and market risk. The two studies make an interesting match to relate analyst recommendations which reflect fundamental information and strictly statistical stock price co-movement in a context of pairs trading. Statistical pairs trading has not been related to analyst recommendations earlier. In this study I provide fresh evidence on the relation between statistical pairs trading and analyst recommendations. My findings provide new information on the relative post-recommendation stock price drift between two stocks forming a pair and how fundamental changes between companies proxied by analysts' relative recommendations affect statistical pairs.

This thesis studies the relation between divergent analyst recommendations and statistical pairs trading. By first performing statistical pairs trading along the strategy in Gatev et al. (1999) and then matching the trading with divergent recommendations as described in Yu (2011) I examine how single statistical trades are related to divergent recommendations. Specifically, I study how relative post-recommendation stock price drift between two stocks forming a pair affects the statistical stock pairs and what implications it has on pairs trading. In addition, I provide evidence and characteristics about statistical pairs trading and relative analyst recommendations between stocks within an industry. My sample spans from year 2000 to 2010 including United States based utility sector stocks and analyst recommendations to the stocks.

My findings are consistent with results presented in previous papers. With significant results I find statistical pairs trading generating positive excess return before transaction costs. The excess return does not survive an estimate of transaction costs, however. I find that analysts' level recommendations provide some valuable information to investors, but that relative recommendations are far more informative. Between two stocks in a statistically formed pair analysts on average can distinguish the relative winner. However, divergent recommendations are not a driver of the positive excess returns, but rather act as a signal of a statistical pair breaking up which leads to negative returns. Pairs do not evidence relative post-recommendation drift in the direction of divergent recommendations within two months of the announcement of recommendations. Neither is the drift consistent within one year of the announcements. Pairs that are not issued divergent recommendations are the main driver of positive abnormal return to statistical pairs trading.

The rest of the paper is organized as follows. Section 2 is a literature review of the closely related studies on pairs trading and analyst recommendations. Based on theory and earlier research I construct my hypotheses in section 3. In section 4 I describe and justify the used data and methodology. Section 5 presents the empirical findings and section 6 concludes the study.

2. Literature review

2.1. Introduction to pairs trading

Pairs trading is a well-known trading strategy among Wall Street brokers, hedge funds and investment banks' proprietary trading desks. It is a simple trading strategy consisting of two assets that have represented co-movement and a relationship between the assets can be estimated. When the assets deviate from the estimated relationship the relatively poorly performed asset is bought and the relatively well performed one is sold short. When the asset prices converge back to the relationship and the poorly performed asset catches up (or the well performed asset regresses), the positions are closed and profit made.

There are many reasons why pairs trading has gained popularity among practitioners. The strategy is market neutral as you have equal long and short positions and you only trade the spread between the pair. Pairs trading is self-financing as gains from short selling balance the capital requirement for the long position. Pairs trading also eliminates the need to analyze the absolute pricing of securities as the spread between a pair only matters. The simplicity of the basic idea captures attention and as the strategy can be unlimitedly modified to include qualitative and quantitative as well as statistical and fundamental information, the strategy has found a wide supporter base.

2.2. Contrarian trading strategies

Pairs trading is a contrarian trading strategy where you buy the loser and sell the winner. The success of contrarian trading challenges the weak form of the efficient market hypothesis. Hence the effectiveness and reasons for the success of contrarian strategies have been studied in large amounts since the 1990s. The results of different studies on stocks are contradictory some finding contrarian investing profitable and some finding evidence of momentum in stock prices. Whether contrarian investing can produce consistent abnormal returns or why it sometimes does is continuously under debate. Contrarian investing is usually affiliated with speculating on short-term price reversals. Jegadeesh (1990) finds highly significant negative first-order autocorrelation in monthly stock returns and Lehmann (1990) arrives at the same conclusion with weekly returns, though not with longer time periods. De Bondt and Thaler (1985), however, show that contrarian investing can be profitable also in long-term. They study returns from contrarian investing with group formation and investment periods of 3 to 5 years and find that stocks that performed poorly over the formation period gain higher returns during the subsequent investment period.

Divergent interpretations of De Bondt's and Thaler's (1985) results have been expressed suggesting that the results can be explained by systematic risk (Chan, 1988) and size effect (Zarowin, 1990). Furthermore, Jegadeesh and Titman (1993) note that a momentum long-short portfolio of long past winners and short past losers produces positive returns in each 12 months after the formation period with a notable exception being the first month where the returns are negative, though not statistically significant. This observation advocates the short-term nature of contrarian investing.

In their early work Gatev et al. (1999) choose a pairs formation period of 12 months and a trading period of 6 months. Due to the construction of my study I will stick to the chosen limits. Hence, my study reflects the more comprehensively documented short-term contrarian effect even though Gatev et al. (2006) find that their positive returns are not driven by short-term price reversals, but due to finding adequate pairs. Important implications from contrarian investing can be, however, linked to pairs trading. Lehmann (1990) notes that short-term price changes provide only little information about long-term price differences compared to fundamentals. This is one of the key ideas in pairs trading, because we are trying to exploit temporary mispricing.

2.3. Statistical pairs trading

Pairs can be chosen with an unlimited amount of criteria; one of the most common in literature is estimating statistical probabilities from the past price series. Hence, pairs trading is often referred to as a statistical arbitrage strategy. Most notable research paper in the field is by Gatev et al. (1999) where they execute a simple statistical trading strategy based on past price movements (presented in detail in section 2.3.1) with U.S. stocks between years 1962-1997 and find annual excess returns of up to 12%. Gatev et al. (2006) extend their research with a genuinely out-of-sample test when they lengthen their time period to cover up to year 2002 of data. Employing the exact same method they find that for period 1999-2002 the annual average excess return is 10%. For the full sample from 1962 to 2002 annualized excess returns average 11%. The out-of-sample results mitigate the data snooping problems inherent in pairs trading research.

After since many scholars have complemented Gatev et al. (2006) by extending their work to include different markets or by executing different pairs trading strategies. In particular Do and Faff (2010) using the same methodology extend the trading period to year 2008 and find shrinking profits in the most recent years as was discovered also by Gatev et al. (2006). Do and Faff (2010) find that smaller returns are not due to increased hedge fund activity as suggested by Gatev et al. (2006), but due to increased fundamental risk in the strategy as a larger number of pairs do not exhibit convergence that would enable profit making. This observation contradicts with Gatev et al. (2006) who conclude that the abnormal returns are compensation to arbitrageurs for enforcing the Law of One Price that assets with similar characteristics should have the same price. The finding by Do and Faff (2010) challenges the usefulness of pairs trading strategy created by Gatev et al. (2006). Results question the relevance of the Law of One Price acting as enforcer of the strategy. If a larger number of pairs do not converge, they can be assumed not to be similar in the context of the Law of One Price. That said, the economic reasons, if any, for the abnormal returns to the strategy remain uncovered.

There is large interest to find economic justification for abnormal returns to statistical pairs trading. The excess returns contradict with weak form efficient market hypothesis and can't be explained with market frictions such as trading costs or short selling constraints. As the excess profits are unexplained and contradict with the weak form of the efficient market hypothesis, scholars have had interest to test statistical pairs trading strategies under different settings in search for more accurate information about the phenomenon. Next I will discuss the existing literature on statistical pairs trading.

Despite the documented declining profits, many papers have found pairs trading profitable under different settings in recent years. With a similar method to that of Gatev et al. (2006) Perlin (2009) finds positive excess returns in the Brazilian stock market in years 2000-2006. As did Gatev et al. (2006) Perlin also finds the strategy market neutral suggesting that pairs trading could provide diversification benefits to an investor.

Mori and Ziobrowski (2011) reproduce the method used by Gatev et al. (2006) in a comparison between pairs trading with common listed stocks and listed real estate investment trusts (REITs). They study period 1987-2008 and find that REITs produced larger abnormal returns over the period from 1993 to 2000. They propose that the effect is due to the characteristics and regularization of REITs, because of which REITs are more homogeneous than stocks on average. Hence, better pairs with long-term relationships can be formed and the pairs are more appropriate for pairs trading. However, after year 2000, REITs don't exhibit larger abnormal profits than common stocks. This could be explained by market recognition of the mispricing, according to Mori and Ziobrowski (2011). A similar argument about homogeneity can be used in utility stocks which produce most of the positive abnormal returns in Gatev et al. (2006) and Do and Faff (2010).

Due to their generality, liquidity and simplicity, current research is mostly concentrated on stock markets. There are, however, some studies on pairs trading with other asset classes. Nath (2003) successfully tests the method by Gatev et al. (1999) for pairs trading with U.S. treasury securities. He finds that during 1994-2000 the strategy produces abnormal returns compared to various benchmarks. Kanamura, Rachev and Fabozzi (2010) apply a pairs trading strategy to energy futures market between 2000 and 2008. They model the futures' price spread as a mean-reverting process and find that stable profits can be made by pairs trading.

In addition to the distance trading method by Gatev et al. (2006), two other acknowledged pairs trading methods have been documented. Vidyamurthy (2004) explains a statistically more coherent method based on cointegration between two assets. The other commonly referred method is by Elliott, van der Hoek and Malcolm (2005). They document a method known as stochastic spread method where they model the spread between two assets' prices as a predictable mean reverting process.

Cointegration and stochastic spread methods are very little tested in academic literature compared to the distance method. Bogomolov (2010) tests the returns of the three methods in the Australian stock market during 1996-2010. He finds significant abnormal returns for all the three methods before transaction costs. After accounting for transaction costs cointegration and stochastic spread methods were unprofitable and distance method produced only minimal returns. In line with other studies Bogomolov (2010) finds all three strategies market neutral. I focus my study on the distance method which is the most studied of the three methods also with out-of-sample data. Moreover, the qualitative characteristics of the pairs match well with Yu's (2011) study about pairs trading on divergent analyst recommendations.

2.3.1. Distance method for pairs trading

In academic articles widely used distance method for pairs trading was originally introduced in academic literature in Gatev et al. (1999). The paper presents a statistical arbitrage method for pairs trading violating the weak form of the efficient market hypothesis. The trading method is market neutral, self-financing and the abnormal returns survive conservative transaction costs and are not driven by bid-ask bounce, short-term price reversals, mid-term momentum or explained by the other two factors by Fama and French (1996): return to small market capitalization stocks or value stocks. Afterwards Gatev et al. (2006) provide an out-of-sample test for their results to eliminate data snooping problems.

The distance method for pairs trading is purely based on stock price co-movement. Identify stocks that have moved together in the past and when they deviate from their relationship, sell the relative winner and buy the relative loser. When the stock prices converge back to the relationship, close the position. Effectively the spread between two stock prices is traded. Profit is made when the spread converges back after a deviation.

Stocks that move together are identified from a wide space of stocks. The pairs are formed during an estimation period by matching stocks that minimize the sum of squared deviations between the stocks' normalized price series including re-invested dividends. The price series are normalized to eliminate the level difference in the sum of squared deviations calculations. The number of eligible tested pairs is $n*(n-1)/2$, where n is the total number of shares.

The top pairs with the smallest sums of squared deviations are traded during a trading period. A position is opened when the spread reaches a pre-specified threshold value and closed when the spread converges back to a pre-specified value. The threshold levels to open and close a trade can be specified in for example standard deviations estimated from the realized spread.

Within the basic framework several trading rules can be altered. Minimum price and liquidity measures as well as fundamental factors can be required in the selection of stocks. The pairs estimation and trading periods’ lengths as well as the number of pairs traded and the re-estimation interval can be altered. Different threshold levels for divergence and convergence can be set and maximum holding periods or stop-loss rules applied.

Strengths of the distance method include simplicity and modifiability. Largest drawback is that the method is highly dependent on the chosen space of stocks. If the stocks are really different, even the closest pairs may not witness close absolute co-movement even though being the closest pair of the sample, which can lead to trading with poor pairs as Do and Faff (2010) remark. This can be prevented with a comprehensive set of stocks which in turn leads to laborious calculations. And on the other hand too close pairs may not deviate enough to allow for trading at all or the absolute divergence might not be large enough to cover for transaction costs even if the pair converges, as Gatev et al. (2006) note.

In their work Gatev et al. (1999) assign values to different parameters arbitrarily. Chosen estimation period of 12 months, trading period of 6 months, re-estimation interval of 1 month, number of traded pairs 5 and 20, divergence threshold to open a trade of 2 standard deviations and convergence threshold to close a trade of 0 standard deviations are not properly tested for feasibility since they were initially arbitrarily assigned. Gatev et al. (2006) and Do and Faff (2010) use the same variable values in their out-of-sample tests.

Various studies have addressed the restrictions and constraints of the presented statistical pairs trading strategies. In search for a solution to these issues mathematically more sophisticated methods have been proposed by some scholars e.g. Huck (2009, 2010), Lin, McCrae and Gulati (2006) and Jurek and Yang (2007). New problems often involved in these attempts are difficult modeling, losing the practicality, inability to interpret the results and data snooping problems. Alongside the statistical trading another school of pairs trading has emerged basing their research on fundamental information such as accounting information, macro-economic development and news flow. Fundamental information as a basis for pairs trading does not include many of the problems inherent in statistical arbitrage models. When statistical models often overlook the economic justification, models based on fundamentals reflect this exact information. The next section provides a review of the existing literature on pairs trading in the context of fundamental information.

2.4. Fundamental information and information shocks in pairs trading

Only until recently academically documented pairs trading research has been mainly about statistical arbitrage. After the decline in profits from simple statistical pairs trading due to faster-paced trading, more cost-effective execution and increase in arbitrage activity for example, research on pairs trading has increasingly started to concentrate on fundamental information. The economic reasons for the existence of profitable pairs trading opportunities has become more and more interesting displacing the traditional research on how to best benefit from the phenomenon. The existing research in the context of pairs trading covers topics under quarterly earnings announcements and analysts' earnings forecasts (Papadakis and Wysocki, 2008), analysts' recommendations (Yu, 2011), firm-specific and industry specific news, analyst coverage, institutional holding, liquidity, macro-economic risk-factors (Engelberg, Gao and Jagannathan, 2009), attention distraction (Jacobs and Weber, 2011) and supplier-customer relationships (Cohen and Frazzini, 2008). Next I discuss the existing research on fundamentals in detail.

New information can create fast and large movements in stock prices. I refer to these kinds of events as information shocks. Information shocks depending on the situation can provide good opportunities for pairs trading with a large divergence from the relationship or they can also create false opportunities by changing or destroying the relationship in a way that the pair never converges and the trade makes a loss. In a case where a position is open during an information shock the outcome may result in larger or smaller returns, respectively. Because of the double-edged sword effect, information shocks provide opportunities and threats and one needs to be extra careful in trading around information shocks.

Papadakis and Wysocki (2008) study the impact of earnings announcements and analysts' forecast revisions on pairs trading with U.S. stocks in 1981-2006. Applying the distance method in pairs formation they find that these information announcements have significant effect on pairs trading. Pairs trading is often opened close to earnings announcements or analysts' forecast announcements. Furthermore, they find that pairs trades opened after announcements are less profitable than pairs trades opened without an effect from information events. This may have implications on analyst recommendations since announcements provide new information which becomes visible in recommendations. Divergent recommendations may then indicate divergence in the pair based on new information.

Finally, Papadakis and Wysocki (2008) find that delaying closing of pairs after earnings announcements or analysts' forecasts results in significantly higher returns. All in all their findings show evidence about drift in stock prices after earnings announcements. This drift indicates that earnings announcements and analysts' earnings forecasts do have significant effect on the returns to an unrestricted pairs trading strategy proposed by Gatev et al. (1999). Accordingly the result information in companies' earnings announcements or analysts' forecasts can be taken into account in opening and closing of pairs positions. It seems that divergence after news is a sign of a broken relationship between a pair. Because trades are better closed after analysts' forecast announcement, it also seems that analysts issue forecasts based on divergence and with the forecasts they accelerate convergence. However, the authors don't study the contents of the new information. Whether the reported earnings are expected or surprising either negatively or positively is not studied. Neither is the content of analysts' forecasts whether positive, negative or neutral taken into consideration.

In a recent study Yu (2011) studies analyst recommendations. She develops a new method for pairs trading based solely on analysts' recommendations. The method does not use any statistical properties of the stocks. Pool of which pairs are picked is formed by placing all stocks in a matrix by their industry and size-class. A pairs trade is triggered when the same analyst gives simultaneously divergent recommendations (buy and hold, hold and sell or buy and sell) for two stocks within the same industry and size category. A long position is taken in the stock that receives more favorable recommendation and a short position in the stock that receives less favorable recommendation. Hence, the strategy is dependent on single analysts' recommendation accuracy and timing. Yu (2011) finds analysts' recommendations to have investment value during her sample period 1994-2009. She also finds her pairs trading based on analysts' recommendations to generate positive risk-adjusted excess returns of 2.2% in 6 months. Yu (2011) does not describe an exact trading strategy since she does not define a rule for closing trades. She only has a rule for opening trades and tests the returns for different time periods. She finds the returns statistically significant on periods of 1, 3 and up to 6 months.

The above mentioned studies have focused on firm-specific information shocks. Another category is the information that affects the market as a whole or companies within a specific industry for example. However, as Papadakis and Wysocki (2008) also discuss, information perceived as firm-specific may often include relevant fundamental information about other companies as well. Hence, the information shock may affect both stocks in a pair, especially since pairs are often formed of companies within the same industry and size. The spillover effect within an industry is documented in for example Foster (1981) and Ramnath (2002). In addition Cohen and Frazzini (2006) provide evidence of the spillover effect in a supplier-customer relationship with companies from different industries. Pairs trading can also be implemented with such companies, if the link between the companies is strong enough.

Cohen and Frazzini (2008) identify strong supplier-customer relationships and test their pairs trading potential. They find that a pairs trading strategy short selling the suppliers' stocks whose customers' stocks had the largest negative returns in the recent month and buying the suppliers' stocks whose customers' stocks had the largest positive returns in the last month yields significant abnormal return of 18.6% per annum. Findings support the view that stock prices evidence drift after initial underreaction to information. The findings provide also results about the spillover effect over industry boundaries as on average 77% of the pairs are from different industries.

Similar to general information shocks, the effect to pairs trading from information spillover depends on characteristics of the stocks. If both stocks react quickly to the information, there might not be any divergence to take advantage of. On the other hand if other company reacts to the information faster and the other with a slow drift, there might be a very profitable fast converging pairs trading possibility.

Engelberg, Gao and Jagannathan (2009) study the difference in pairs trading returns whether the initial divergence is due to firm-specific (idiosyncratic) news or industry-level shocks. Applying the distance method to pairs within the same industry they find that returns are lower when the initial divergence is due to news affecting the value of only one of the stocks in a pair. In such a case the divergence is more likely to be permanent and not result in a profit. This result indicates that an investor should not trade a pair that diverges after firm-specific news. It also provides evidence that the spillover effect is not common in a pairs trading framework. Finally, the profitability is highly dependent on the liquidity characteristics of the stocks in a pair, and especially how the characteristics differ. Information shocks that produce positive returns are those that temporarily reduce liquidity of one of the stocks in a pair or that affect both stocks, but other reacts faster. As a general rule, the more liquid stocks that react faster to common shocks are from larger corporations with more sell-side analyst coverage and larger institutional holdings. An optimal pair appears to be a closely related pair within the same industry, but other company large and liquid and the other small and less liquid.

Jacobs and Weber (2011) research pairs trading returns in different information settings. They study the effect of large flows of general information distracting market participants from analyzing firm-specific information. An underlying assumption is that in a case of important general news, market participants focus on the effects of the general news instead of analyzing firm-level information as they do when there aren't other distractions. The disregard of firm-level information leads to inefficiencies as market participants don't focus on keeping the relative prices of securities in line. As a result divergences from assets' relationships merge. Jacobs and Weber (2011) test the hypothesis in U.S. as well as in eight other major stock markets. Following the distance method in pairs formation they find that pairs opening on high distraction days produce significantly higher returns than pairs opening on low distraction days. The probability of pairs converging faster is also higher for pairs opening on high distraction days. The phenomenon holds for other perceived market inefficiencies such as investors having smaller attention on weekdays before holidays, Fridays (DellaVigna and Pollet, 2009) and down market periods (Karlsson, Loewenstein and Seppi, 2009). In line with Jacobs and Weber (2011), Peress (2008) finds that media coverage has less influence on immediate returns and post-announcement drift for individual stocks on days with high distraction than on days with low distraction.

The results of Engelberg et al. (2009) and Jacobs and Weber (2011) underline the importance of the reason for divergence in stock prices. The results point to following market- or industry-wide news as reason for divergence instead of firm-level news. Their results also emphasize the fact that the reason for divergence dictates the probability of convergence.

2.5. Analyst recommendations

Previous section introduced the existing research on pairs trading. A common feature to almost all the cited papers is that they argue for the economic justifications for the success of statistical pairs trading. A study by Yu (2011) does not take a stand on statistical pairs trading, but instead finds a pairs trading strategy based solely on divergent analyst recommendations generating excess risk-adjusted return. In this study I examine the possible effects of the phenomenon found by Yu (2011) on the statistical pairs trading strategy described in Gatev et al. (2006) and studied by several scholars without yet to recognize the underlying economic reasons. Recommendations reflect information in both fundamentals and stock prices, which makes them an interesting match to purely statistical trading. Next I review the related studies' findings about analyst recommendations.

There are several frequently cited papers that conclude that analyst recommendations, if interpreted correctly, can have information value to investors, e.g. Jegadeesh, Kim, Krische and Lee (2004), Elton, Gruber and Grossmann (1986), Womack (1996) and Barber, Lehavy, McNichols and Trueman (2001). The results are the same that my main reference paper Yu (2011) concludes.

2.5.1. Level recommendations

Elton et al. (1986) find investment value in analyst level recommendations by examining broker houses' buy and sell lists. On average buy list returns 0.80 %-points more monthly than the sell list. Barber et al. (2001) study more closely trading strategies based on consensus level recommendations. They find that recommendations do have investment value, but capitalizing on recommendations requires fast reaction to changes and leads to high trading which in effect leads to high trading costs. After accounting for trading costs Barber et al.

(2001) do not find trading strategies based on consensus recommendations profitable. Womack (1996) points out that information analysis and issuing recommendations is costly and researchers must be compensated; one part of the compensation comes from commissions from trading stocks. Because the reaction to changes in consensus recommendations needs to be within days, the abnormal return can be attributed to recommendation changes as opposed to simple level recommendations.

In contrast to the findings of Barber et al. (2001) Jegadeesh et al. (2004) find that consensus level recommendations do not always add value. They also find that positive performance of recommendations is driven by momentum factors. The value in the absolute recommendations is not unambiguous. One significant source of influence on recommendations has found to be analysts' bias when issuing recommendations.

2.5.2. Bias in recommendations

Sell-side equity analysts who issue investment recommendations for listed securities are under the pressure of conflicts of interest arising from career concerns and compensation. Vast majority of analysts issuing recommendations are sell-side analysts. Conflicts of interest are between issuing objective forecasts and recommendations and issuing forecasts and recommendations that are beneficial for their employer and thus for themselves. Conflicts of interest often induce analysts to issue overly optimistic forecasts and recommendations. Many studies have found analyst recommendations to contain bias towards more positive recommendations. Michaely and Womack (2005) provide a comprehensive review of literature up to year 2002, theory and practice of analyst forecasts and recommendations, conflicts of interests and biases. To demonstrate the problem in applying level recommendations in trading I discuss the most relevant themes brought forward in Michaely and Womack (2005) as well as refer to relevant new studies on analyst recommendations and bias.

Issues affecting analyst recommendations are eclectic, but predominantly the pressure is to issue overly optimistic forecasts or recommendations. Hong and Kubik (2003) find that brokerage houses reward optimistic analysts. With a comprehensive sample of 12 000 analysts and 600 brokerage firms between years 1983 and 2000 they find that the accuracy of analyst forecasts matters for their career advancement, but also that relatively optimistic analysts have more favorable career paths. In addition, they find that analyst forecasts are judged less on accuracy and more on optimism when a stock underwritten by their employer is in question. The optimism is rewarded presumably, because optimistic analyst reports generate investment banking business and trading commissions as discussed in e.g. Michaely and Womack (2005). In line with theory that conflicts of interests cause a positive bias, Carleton, Chen and Steiner (1998) find that sell-side analysts issue more optimistic recommendations than buy-side analysts. Uniformly they find that buy-side analysts predict investment performance more accurately than sell-side analysts.

Michaely and Womack (1999) find that analysts do act accordingly to findings in Hong and Kubik (2003) and issue more favorable recommendations when the stock is underwritten by their employer. The effect is not driven by better analyzing skills or superior information, since the stocks positively recommended by underwriter-related analysts significantly underperform the stocks positively recommended by nonunderwriter-related analysts. The bias is not the only plausible explanation. Underwriter analysts' genuine believe in the stocks or selection bias cannot be reliably ruled out. It can be that share issuers select those investment banks as underwriters whose analysts have the most positive view about the share issues.

Firth, Lin, Liu and Xuan (2011) study the effects mutual fund relationships have on analysts' recommendations. Since mutual funds bring a large proportion of brokers' trading commissions, broker firms have incentives to please the mutual fund managers. Firth et al. (2011) find that analysts issue more favorable recommendations to stocks that are in the portfolios of mutual funds from which they get brokerage business. Optimism is positively related to the weight of the stock in the mutual funds' portfolios and to the amount of brokerage commissions the mutual fund generates. They also find evidence that the results are not due to mutual funds following recommendations of brokerages they do most business with, but due to pressure from mutual funds that already hold the stocks in question.

Kolasinski and Kothari (2008) study analysts' biases in M&A deals. They find that analysts affiliated with the advisor of the acquirer are more likely to upgrade their recommendation for the acquirer stock than unaffiliated analysts. The optimism is strongly explained by the bias analysts have to issue favorable recommendations to stocks that bring their company advisory business. Cicero, Kalpathy and Sulaeman (2010) find that analysts bias their recommendations to induce corporate borrowers to their lending arm. They find that companies are more likely to borrow from banks whose analysts issue favorable recommendations in expect to be able to borrow cheaper from a favorable bank.

Previously mentioned papers provide evidence of the conflicts of interest introducing biases that distort recommendations from analysts' objective opinions. Lim (2001) suggests a different view on the reasons for the positive bias. He suggests that analysts have a rational positive bias in their forecasts which is attributed to the objective of producing as accurate forecasts as possible. Positive analysts have better access to companies' management for information which in effect leads to more accurate forecasts. Lim (2001) creates a model that evaluates forecast error as a function of bias, accuracy and available information. He finds that positive bias may be optimal to reach accurate forecasts.

Even though positive bias is the consensus conclusion, there are also differing findings. Clarke, Ferris, Jayaraman and Lee (2006) find that analysts do not issue optimistic recommendations to financially distressed companies with which they have an investment banking relationship. Chan, Karceski and Lakonishok (2003) provide evidence that analysts have in fact bias to issue pessimistic forecasts. Due to many reasons, e.g. to attract investment banking business, analysts want to be in the favor of the management of the companies they cover. Managers on the other hand want to beat analysts' earnings forecasts. In these situations the managers and analysts have a common interest to match earnings to forecasts. If the company is falling short of forecasts, analysts can revise their forecasts disproportionately downwards before the earnings announcement to let the company exceed forecasts.

The reviewed literature argues for a bias in analyst recommendations. For a detailed analysis on the diversified issue of bias in analyst recommendations I refer to Michaely and Womack

(2005) and a deeper look into the cited articles. The important conclusion to be drawn is that recommendations are affected by conflicts of interest and that they are most likely positively biased. Hence, level recommendations are noisy and for an investor it is better to look at relative recommendations that may contain more information. In the cited papers e.g. Kolanski and Kothari (2008) find that recommendation changes provide more informative results and are economically more meaningful than simple level recommendations.

2.5.3. Relative recommendations

The problems in level recommendations have led to research on relative recommendations. Most studied form of relative recommendations is the relation of recommendations in time i.e. changes in recommendations. Studying recommendation changes instead of absolute recommendations eliminates the problems of stickiness and partly the bias to issue better recommendations.

Elton et al. (1986) find investment value in recommendation changes. They also find investment value in level recommendations, but excess returns are larger, when changes in recommendations are reviewed rather than only level recommendations. They attribute this to the stickiness of recommendations. Analysts are not eager to change their recommendations and hence a recommendation change implies material new information about the company, whereas the level recommendation is sticky and might put too much weight on old information. Womack (1996) finds similar results studying additions and removals of stocks from the buy and sell lists of brokerage houses. He finds that analysts do possess market timing and stock picking skills and that positive abnormal return can be gained by following additions to buy and sell lists. Jegadeesh et al. (2004), who find that consensus level recommendations do not add value, also find that recommendation changes contain valuable information to investors. Brav and Lehavy (2003) conclude that the magnitude of recommendation change conveys also valuable information. E.g. recommendation change from hold to strong buy is associated with larger abnormal returns than change from hold to buy.

Another form of relative recommendations is recommendations relative to industry consensus or peers within the same industry. Since analysts often specialize in a given industry, and use relative valuation techniques, they are well positioned to issue relative recommendations even though the absolute recommendations may be affected by biases or weak ability to analyze market or macro information. Hong and Kubik (2003) note that average analyst in I/B/E/S database follows 9.3 companies in a year and hence has a view on the relative superiority of the companies. Da and Schaumburg (2011) analyze a long-short trading strategy based on expected return implied by analysts' target prices and the prevailing stock price between 1997 and 2004. Similar to the pairs trading method I employ, the long-short strategy involves buying short-term losers and selling short-term winners. They find that investors can get more information by comparing analysts' reports between stocks within the same industry than between all stocks. They find that analysts are unable to forecast market return or relative return to different industries, and that absolute target prices are not as informative as target prices relative to industry peers. Similar to Gatev et al. (2006) and Do and Faff (2010) find for statistical pairs trading, Da and Schaumburg (2011) find lower returns to the strategy in the beginning of the 21^{st} century than in the end of the 1990s.

In pairs trading stocks are priced relative to each other. When issuing recommendations analysts frequently use valuation multiples within an industry as a basis for their analysis. Asquith, Mikhail and Au (2005) document that 99.1% of analysts use earnings multiples in valuation. Multiples based valuation is relative valuation between stocks within the same industry. If the method is a valid one to value shares and analysts issue their recommendations accordingly, then relative analyst recommendations within an industry are valuable to investors. This has strong implications on pairs trading based on divergent recommendations.

Boni and Womack (2006) test analysts' ability to rank stocks within an industry. Their findings tie together research about consensus level recommendations, recommendation changes and relative recommendations between peers and industries. Studying years from 1996 to 2002 they find that analysts' level recommendations even within an industry do not have valuable information content. They also find that analysts do not have ability to predict the winner and looser industries when comparing industry consensus level recommendations. The finding is in line with theory that analysts issue recommendations to stocks within an industry and they have bias to issue buy recommendations. Boni and Womack (2006) find most value in analyst recommendations when changes in recommendations are compared between stocks within an industry. Conclusion from their study is that analysts are experts in the industry they specialize, but their level recommendations are affected by biases. Hence, analysts express their relative opinions about companies (and investment value can be found) in relative recommendation changes between companies.

Yu (2011) tests relative recommendations from individual analysts. She trades pairs of stocks where she matches stocks belonging to the same industry and size class. Pairs are traded based on newly announced divergent recommendations for the stocks issued at the same time by the same analyst. She finds the strategy producing excess returns and thus single analysts' relative recommendations are valuable to investors.

2.5.4. Stock price drift after recommendation announcements

Most of the above mentioned studies use daily closing prices implying that by following analyst recommendations it is possible for an investor to gain positive abnormal returns. This conclusion violates the semi-strong form of the efficient market hypothesis that all public information is reflected in the market prices immediately. For the purposes of this study it is important to examine how quickly the gains from following recommendations diminish after the recommendation is announced i.e. how fast does an investor have to react to recommendation changes in order to benefit from the post-recommendation stock price drift.

Barber et al. (2001) study the matter and note that stock price reactions to recommendation changes are not instant, but the drift is very short-lived and possible gains diminish in less than a week for stocks with buy recommendation and in one month for sell recommendations. Elton et al. (1986) find that information from a recommendation change is fully absorbed in the stock price within three months. They see that there is a problem with following sticky level recommendations as a stock holds a certain recommendation for a too long period. Therefore, they conclude that excess returns that can be earned by buying a recommended list at any point in time disappear within two months. Womack (1996) and Jegadeesh et al. (2004)

find similar results. Womack (1996) concludes that for the new buy recommendations excess returns diminish during the first month and for new sell recommendations during the first six months. Jegadeesh et al. (2004) find that excess returns earned from recommendation changes occur in the first three to six months.

Yu (2011) finds that risk-adjusted positive returns to pairs trading according to analyst recommendations are statistically significant up to 6 months after the recommendation announcements. Yu's (2011) and the above mentioned papers' results are interesting in relation to statistical pairs trading strategy by Gatev et al. (1999). Gatev et al. (1999) use a 6-month trading period in their trading strategy and hence the same effect that is present in analyst recommendations, if any, is likely to be present in the strategy. Furthermore, Gatev et al. (2006) find that both stocks in most pairs are close to each other in size and mainly both belong to the same industry. This strengthens the base for the joint study since Yu (2011) also tested pairs from the same industry and size-class. I study newly announced recommendations. Part of announced recommendations are changed recommendations and part repetitions of the existing recommendations. Hence my study is neither about changes in recommendations nor about pure level recommendations, but something in between. Goal is to study whether the same effect that is in recommendation announcements according to the study by Yu (2011) is present in the statistical pairs trading by Gatev et al. (1999).

3. Hypotheses

I study whether relative analyst recommendations affect the returns to statistical pairs trading by incorporating fundamental information to the pairs or through price drift that the recommendations themselves cause. I form my hypotheses on the basis of theory and results from earlier research.

First I study the statistical trading with a recent set of data. Gatev et al. (2006) and Do and Faff (2010) find that statistical pairs trading with the distance method generates positive abnormal returns. They both show utility sector stocks to yield the largest positive abnormal returns when traded in statistical pairs. Utilities have the fundamental properties for long-term stable relationships and are therefore well-suited for short-term pairs trading. I study pairs trading with a sample of utility stocks applying a similar distance method as Gatev et al. (2006) and Do and Faff (2010). The expectation is that trading results in positive abnormal returns. Hence, my first hypothesis:

H_1: Statistical pairs trading generates positive abnormal returns.

Secondly I test the investments value in relative analyst recommendations. Relative analysis between stocks within same industry has been found informative in Papadakis and Wysocki (2008) and recently Yu (2011) found that relative recommendations between a pair of stocks belonging to the same industry and size class are valuable to investors. Drift in stock price after an issue of new recommendation has been estimated to last from one week up to six months. I test consensus recommendations on a 6-month period between two stocks forming a statistical pair. Based on earlier studies about recommendations and stock price drift, and theoretical background for value in relative recommendations, I expect to find relative recommendations valuable to investors. I arrive at my second hypothesis:

H_2: Analysts' relative recommendations have investment value.

Finally I study the effects relative recommendations have on statistically traded pairs. For the recommendations to drive positive abnormal returns to pairs trading, hypotheses 1 and 2 should be accepted. Specifically, I study whether divergent recommendations, being differing recommendations issued by a single analyst for two stocks forming a statistical pair, affect the statistical pairs. My definition measures well with the definition of divergent recommendations in Yu (2011).

Divergent recommendations can affect the pair in two ways: by enlarging the spread between the two stocks or by narrowing the spread. This can result in multiple implications on returns to pairs trading depending on the timing of the recommendations and the direction of the pairs trade. Assuming recommendations reflect correctly fundamental information and that markets act accordingly, if divergent recommendations are given before the opening of the trade, they cause the spread to widen up to the trigger point of opening a pairs trade. These trades are expected to yield negative returns since the statistical pair has separated due to fundamental information, which is according to findings in Papadakis and Wysocki (2008) and Engelberg et al. (2009). The spread may continue to widen after trade opening or it may find a new equilibrium. In any case the pair does not anymore follow the original estimated relationship.

If recommendations are issued after the opening of the trade, they may cause the spread to widen further or narrow down depending on the direction of the recommendations and the direction of the pairs trade. In the former case analysts are lagging behind the market and the market has already acted on the information before analysts have issued their recommendations. Recommendations accelerate the widening of the spread. Pairs trade yields negative return as the pair never converges and the original relationship does not hold. In the latter case analysts see the spread between the pair being too large and they issue recommendations that narrow the spread. Analysts act as enforcers of the Law of One Price and they have a positive impact on the return to pairs trade since they effectively close the spread.

In summary, the effects of divergent recommendations can be divided into three categories: (1) recommendations issued before the opening of pairs trade and (2) recommendations issued after opening of trade having a direction to widen the spread are expected to have a negative impact on the return and (3) recommendations issued after opening of trade having direction to narrow the spread are expected to have a positive impact on the return. Hence hypothesis 3 on the effects of divergent recommendations on the returns to statistical pairs trading is also divided into three parts:

H_{3a}: Pairs trades opened after announcement of divergent recommendations yield abnormal negative returns.

H_{3b}: Pairs trades that receive divergent recommendations in the direction to widen the spread after the trade is opened yield abnormal negative returns.

H_{3c}: Pairs trades that receive divergent recommendations in the direction to narrow the spread after the trade is opened yield abnormal positive returns.

The aggregate effect of divergent recommendations depends on the relative number of observations in the three categories. If statistical pairs trading yields abnormal positive returns and the market anomaly is explained by divergent recommendations, then divergent recommendations in the direction to narrow the spread issued after opening of pairs trade are expected to dominate.

4. Data and methodology

4.1. Data description

The data consists of daily returns and analysts' recommendations for United States based common stocks from utilities sector for the period 2000-2010. The daily returns are collected from The Center for Research in Security Prices (CRSP) database. Return series are total returns i.e. adjusted for dividends and other cash payments as well as stock splits and mergers. Only stocks with share codes 10 and 11 are allowed to restrict the sample to common stocks. Utilities sector stocks are identified with Standard Industrial Classification (SIC) major group two-digit code 49. The use of share codes 10 and 11 to identify common stocks and use of SIC code 49 to identify utilities is the same approach as in Do and Faff (2010). Stocks that experience one or more days without trades during the pairs formation period are excluded from the data similarly to Gatev et al. (1999). Analysts' recommendations are obtained from Institutional Brokers' Estimate System (I/B/E/S) Details Recommendation database. Daily recommendations are gathered from all analysts for all stocks that I trade from December 2000 to December 2010.

The criteria for data selection need to be justified. The data is selected based on the main aim of the paper: to study the connection of divergent analyst recommendations as discussed in Yu (2011) and statistical pairs trading's returns presented in Gatev et al. (2006). Gatev et al. (2006) report that the positive abnormal return is clearly pronounced within the utilities sector. The reported positive excess monthly return for the top 20 pairs trading strategy is 0.90% and excess monthly return in the utilities sector is 1.08%. Furthermore, the average sector weight of utilities in the whole strategy is 55%. Hence, to understand what drives the positive returns to the strategy, it is important to understand what drives the positive returns within utilities sector. Reported results in Do and Faff (2010) are consistent with those of Gatev et al. (2006). Da and Schaumburg (2011) find that relative target prices are more accurate for stocks with higher fraction of tangible assets. This conclusion is consistent with the selection of utility stocks. Following Gatev et al. (2006) only common stocks and stocks with positive trading volume each day during formation period are included in the sample.

Gatev et al. (2006) study the pairs trading strategy from 1962 through 2002 and Do and Faff (2010) extend the period up to 2008. They both find the strategy profitable, but record declining profits for the most recent years. Nonetheless, positive excess returns have been recorded also in the recent years. In addition, this study is about the effect of analyst estimates which Yu (2011) tested for a relatively recent period of 1994-2009. Da and Schaumburg (2011) point out that in August 2000 SEC adopted Regulation Fair Disclosure before which analysts could have had access to material corporate information not available publicly. Hence, after August 2000 the role of analyst recommendations as information provider has changed. The changes in abnormal returns and analyst recommendations affect my study significantly. In my study I am interested in the current investment environment. To have a validated base for my research and to produce up-to-date results I choose a sample period from year 2000 to 2010.

The full data consists of more than 678 000 daily return observations from over 150 stocks over a period of 11 years. The average number of stocks with positive trading volume every day is 115 and the average number of potential pairs is 6 602 each period. The data is similar to earlier research as Gatev et al. (2006) report average number of utility stocks of 156 during 1962-2002.

The number of analyst recommendations suitable for my study in the I/B/E/S database is 3 126, on average 156 issued new recommendations for top 20 traded pairs during 7 months, starting one month prior to trading period and ending at the trading period end. The total number of recommendations for both stocks in a pair from the same analyst is 305, on average 15 in a trading period, and the number of divergent recommendations is 150, on average 8 in a trading period. On average 25.8% of stocks in the top 20 pairs have no recommendations, which is in line with Boni and Womack (2006) who document that 25.6% of their sample stocks do not have recommendations registered in the I/B/E/S database during 1996 through 2002. Table 1 provides descriptive statistics for the stock and recommendation data used in the study.

The number of stocks with positive trading volume during pairs formation period stays relatively stable throughout the sample period. The number of recommendations in the database increases in time. The number of recommendations, recommendations for both stocks in a pair from same analyst and the number of divergent recommendations all show a rising trend. Mean number of divergent recommendations in a trading period on the first half of sample is 5.6 and on the second half 9.4. This can be attributed to increase in the number of recommendations and development in data collection to cover more brokerage houses as Brav and Lehavy (2003), Lim (2001) and Hong and Kubik (2003) document. The number of recommendations shows also seasonal variation. Number of recommendations is largest in years 2002 to 2003 and from the second half of 2007 to the first half of 2010, the same years equity markets hit their bottoms.

Panel B in Table 1 reports descriptive recommendation statistics divided to pairs' level. Mean number of recommendations during trading period for a pair is 7.9 with maximum of 39 and minimum of 0. Mean number of recommendations from the same analysts for both stocks in a pair is 0.8 and number of divergent recommendations even lower 0.4. The mean number of divergent recommendations during a trading period for all 20 pairs is 8 which is enough for trading.

Table 1

Description of data

Table 1 shows descriptive statistics for the used data from year 2000 to 2010 with 20 6-month trading periods. Panel A shows figures for all trading periods and Panel B for individual pairs. Notation 1/2001 denotes trading period that lasts for the first half of year 2001 and notation 2/2001 denotes trading period that lasts for the second half of year 2001, etc. Recommendation figures are from a 7-month period starting one month prior to trading period and ending at the end of trading period. In Panel A recommendation figures are totals for top 20 pairs and in Panel B figures are for individual top 20 pairs.

	Number of stocks	Number of potential pairs	Mean trading period return for sample stocks	Mean trading period volatility for sample stocks	Number of recommendations for top 20 pairs	Number of recommendations from same analyst for both stocks in top 20 pairs	Number of divergent recommendations for top 20 pairs
Panel A: Trading periods							
1/2001	120	7 140	9.0 %	26.8 %	106	5	2
2/2001	118	6 903	-3.3 %	23.9 %	84	2	2
1/2002	119	7 021	-2.1 %	22.9 %	159	15	8
2/2002	114	6 441	-13.8 %	41.9 %	270	24	10
1/2003	110	5 995	18.7 %	24.3 %	226	36	15
2/2003	110	5 995	15.5 %	20.0 %	147	17	10
1/2004	108	5 778	4.3 %	15.4 %	134	8	5
2/2004	114	6 441	14.6 %	16.5 %	108	9	3
1/2005	113	6 328	11.9 %	16.7 %	117	5	1
2/2005	117	6 786	0.6 %	18.7 %	106	2	0
1/2006	120	7 140	8.8 %	17.3 %	74	3	2
2/2006	120	7 140	15.4 %	13.9 %	155	15	5
1/2007	120	7 140	5.3 %	16.0 %	135	4	1
2/2007	120	7 140	2.7 %	22.6 %	172	15	8
1/2008	116	6 670	-4.8 %	23.0 %	152	18	8
2/2008	114	6 441	-20.2 %	48.2 %	144	22	15
1/2009	110	5 995	-0.2 %	32.3 %	217	31	16
2/2009	114	6 441	16.8 %	21.6 %	223	40	25
1/2010	114	6 441	-4.8 %	20.5 %	196	19	10
2/2010	116	6 670	17.9 %	17.0 %	201	15	4

Continued

Table 1 (continued)

Description of data

	Number of stocks	Number of potential pairs	Mean trading period return for sample stocks	Mean trading period volatility for sample stocks	Number of recommendations for top 20 pairs	Number of recommendations from same analyst for both stocks in top 20 pairs	Number of divergent recommendations for top 20 pairs
Panel A: Trading periods							
Mean	115	6 602	4.6 %	23.0 %	156	15	8
Median	115	6 556	4.8 %	21.1 %	150	15	7
Standard deviation	4	444	10.8 %	8.8 %	52	11	6
Panel B: Pairs							
Mean	na.	na.	na.	na.	7.8	0.8	0.4
Median	na.	na.	na.	na.	7	0	0
Maximum	na.	na.	na.	na.	39	10	6
Minimum	na.	na.	na.	na.	0	0	0
Standard deviation	na.	na.	na.	na.	5.7	1.5	0.9

4.2. Methodology

In pairs formation and trading I follow closely the methodology employed in Gatev et al. (2006). Parts where the study differs from the methods of Gatev et al. (2006) or where I have had to make my own assumptions are pointed out clearly. Pairs are formed over a formation period of 12 months and traded over the subsequent period of 6 months. Afterwards closest 20 pairs eligible for trading are examined for analyst recommendations.

4.2.1. Pairs formation

First I calculate a cumulative value series from the total return series for all stocks. The series are normalized to start from 1 in the beginning of the formation period in order to eliminate level differences in stock prices when calculating squared residuals. Equation 1 states the calculation of the cumulative value series:

$$V_{s,t} = (1 + r_{s,t}) \cdot V_{s,t-1} \,, \qquad (1)$$

where $V_{s,t}$ is the value of stock s at time t and $r_{s,t}$ is the total return to stock s from time t-1 to time t. The first observation $V_{s,0}$ is set to 1 for all stocks.

From the normalized value series each stock is matched with closest pair based on sum of daily squared deviations calculated from the difference of the two stocks' series. Each stock is matched with a pair that minimizes the sum of squared deviations. Sum of squared deviations is calculated as shown in equation 2:

$$SSD_p = \sum(V_{a,t} - V_{b,t})^2 \,, \qquad (2)$$

where SSD_p is the sum of squared residuals for pair p formed from stocks a and b. The matching process results in a vast number of tested pairs. 120 individual stocks form 7 140 potential pairs calculated with equation 3:

$$n_p = n_s\,(n_s - 1) / 2 \,, \qquad (3)$$

where n_p is the number of unique pairs and n_s is the number of single stocks. Each stock is matched with a closest peer resulting in the same number of pairs that we have stocks. These pairs are ranked on the sum of squared deviations and 20 pairs with smallest sums of squared deviations are selected for trading. These pairs represent the closest pairs in the data. A single stock is limited to belong to only one pair. This is done to diversify idiosyncratic risk of having the same stock in multiple pairs.

4.2.2. Pairs trading technique

After the 20 closest pairs are formed, they are traded for the following 6-month period. Trading is based on value series' differences during the trading period and standard deviations of the differences measured during the formation period. The normalized value series are continued to the trading period without renormalizing them in the beginning of the period. Hence, a pair trade may open instantly in the first day of the trading period.

When the value series of a pair differ by more than two standard deviations, a trade is opened. The standard deviation is measured during the 12-month formation period and is kept constant for the whole trading period. A long position is taken in the relatively low valued stock and a short position in the relatively high valued stock in expectation of a convergence of the spread between the two value series. The long and short positions are of equal dollar amount and therefore the trade is self-financing as the positive cash flow from the short position finances the negative cash flow from the long position. When the value series converge back to equilibrium, the spread equals zero, the trade is closed and long position stock sold and short position stock bought. The spread, and thus the magnitude of the standard deviation, determines the maximum return from a trade.

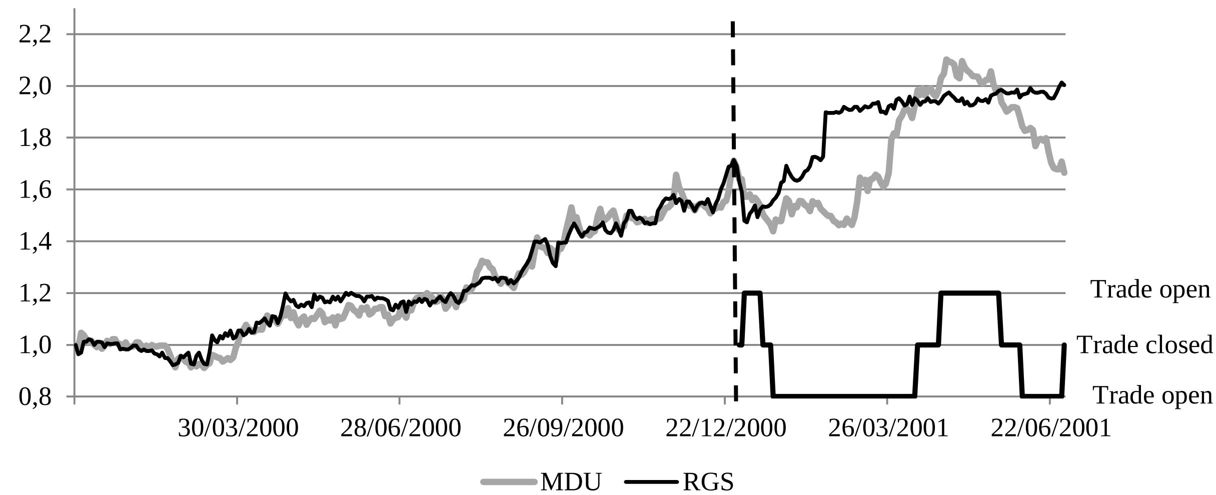
A pair may open and close multiple times in both directions during the trading period. If a pair is opened and does not converge during the trading period, the pair is closed on the last day of trading which may result in a profit or a loss. Another case when a pair may result in a loss is a delisting. If a stock in a pair that is open is delisted, the trade is closed on the day of the delisting using the delisting price. Correspondingly, if a stock in pair that is not open is delisted, that pair is not traded after the event.

Figure 1 provides an illustrative example of the statistical pairs trading. During the formation period the two value series experience only small deviations both showing clearly a rising trend. Due to only small differences the stocks are selected for trading with a small sum of squared deviations. Almost from the start of the trading period 2. January 2001 the value series start to deviate and trade is opened by buying RGS and selling short MDU. On 16. January the trade is closed and on 22. January another trade is opened in the other direction by buying MDU and selling short RGS. Altogether the pair is opened four times during the trading period. First three are profitable when the value series converge, but the last trade produces negative return when the value series diverge further after the trade is opened and eventually the trade is closed at a loss at the end of the trading period.

Figure 1

Trading sample

Figure 1 is an illustrative sample of the statistical pairs trading method. The figure shows the normalized value series set to start from value 1.0 of stocks MDU Resources Group (MDU) and RGS Energy Group (RGS) between January 2000 and June 2001. The third line alternating between values 0.8, 1.0 and 1.2 shows the status of the pairs trade. Value 1 denotes that a trade is not open and value 1.2 (0.8) denotes that a trade is open and MDU sold short (bought long) and RGS bought long (sold short). January-December 2000 is the formation period of the pair and January-June 2001 is the trading period. Vertical dashed line at 2. January 2001 indicates the starting point of the trading period.



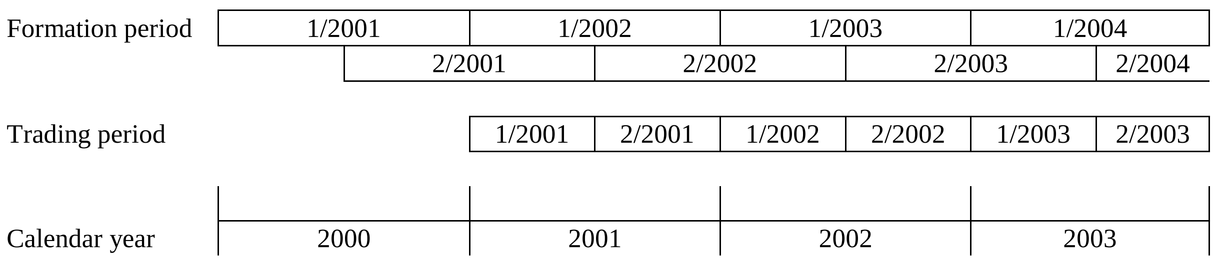
My sample spans from the beginning of year 2000 to the end of 2010. The sample includes 20 formation and trading periods. The first formation period is from January 2000 to December 2000 followed by a 6-month trading period from January 2001 to June 2001. The formation periods are staggered by 6 months the second period being from July 2000 to June 2001.

Formation periods are always followed by a 6-month trading period. Thus, 6-month trading periods run successively covering the complete period 2001-2010 without gaps or overlap. Figure 2 illustrates the alternation of formation and trading periods. This part differs slightly from Gatev et al. (2006). They form pairs on a one-month interval resulting in overlapping trading. Each month belongs to six different trading periods, because every month a new 6-month trading period is initiated. Problem involved is that same stocks may be used simultaneously in same or different pairs, thus exaggerating the results and resulting in risks difficult to measure. The interpretation of results suffers. I employ sequential 6-month trading periods without overlapping trading, thus generating transparent results.

Figure 2

Formation and trading periods' alternation

Figure 2 shows the alternation of 12-month formation and 6-month trading periods. First formation period (1/2001) is the calendar year 2000 followed by the first trading period (1/2001) for the first half of calendar year 2001. The second formation period (2/2001) lasts for the second half of calendar year 2000 to the first half of calendar year 2001, partly overlapping the first (1/2001) and the third (1/2002) formation periods. Second trading period (2/2001) is followed on the second half of calendar year 2001. Trading periods never overlap. The last formation period in the sample is from the second half of calendar year 2009 to the first half of calendar year 2010 and the last trading period for the second half of calendar year 2010 ends the sample.



4.2.3. Return calculation

The percentage return to a self-financing portfolio is not unambiguous. A zero-cost portfolio does not have invested capital to be used in a return calculation. Often used are gross exposure, the long position or the margin required on the short position, but an established method has not been formed. I use the most conservative method for return calculation employing the gross exposure as the "investment".

If 1 dollar position is taken in both the long and the short positions, then the gross exposure amounts to 2 dollars to which the returns are calculated. Gross exposure does not overestimate the returns and this method is also in line with the return calculations in Gatev et al. (2006) and Do and Faff (2010). Yu (2011) calculates returns to the long position which increases her comparable return, but she uses excess return to single stocks compared with market return which decreases her comparable return. Thus, Yu's (2011) returns are not as comparable as those reported in Gatev et al. (2006) and Do and Faff (2010).

Gatev et al. (2006) calculate monthly returns marked-to-market daily with cash flows reinvested during the trading period. As I am interested in single trades and how they compare with analyst recommendations, I will not calculate daily returns, but returns to single trades and from these results I derive the returns to single pairs and portfolios. The return to portfolio during the 6-month trading period enables comparison to the results of Gatev et al. (2006) and especially to Do and Faff (2010) who report their results with a 6-month view.

Return to a single roundtrip pairs trade[1] is calculated as the absolute dollar return to both long and short positions divided by the gross exposure calculated as the dollar amount invested in long position plus the dollar amount shorted. Return calculation to a single roundtrip trade is shown in equation 4:

$$r_i = [(-V_{a,x} + V_{a,z}) + (V_{b,x} - V_{b,z})] / (V_{a,x} + V_{b,x}) , \tag{4}$$

where r_i is the return from trade i, $V_{a,x}$ is the value of stock a bought at time x, $V_{b,x}$ is the value of stock b shorted at time x and $V_{a,z}$ and $V_{b,z}$ denote the values of stocks a and b at the time of closing the trade at time z. The dollar amounts invested in long and short positions are always equal.

Return to a pair is calculated as the sum of returns of all trades executed during the trading period. Since the return to each trade is calculated similarly with the same gross exposure, the

[1] A roundtrip trade is defined as the opening of a pairs trade position and the closing of the position. A roundtrip trade includes 4 individual trades: 2 when opening the position by buying one stock and short selling other, and 2 when closing the position by buying the shorted stock and selling the bought stock.

pair return calculation assumes no reinvestment of cash flows. The underlying assumption is that in every trade an investor wants to take the same magnitude of risk not overweighting trades in the end of a profitable trading period. Moreover, as the initial investment is zero and the invested capital can't be measured, the amount of investment is ambiguous and cash flows do not matter for the gross exposure that can be taken. In a single pair the trades never overlap and the gross exposure is stagnant and the return to a pair is simply the sum of returns from all trades.

Return to a whole portfolio of pairs during a 6-month trading period is calculated as the average of the returns to all pairs that were actually traded at least once during the trading window. The zero returns to pairs that were eligible for trading, but did not at any point differ by two standard deviations, are left out from the portfolio return calculation. Hence, return is calculated to invested capital, not committed capital, though the calculation assumes that capital is tied to a traded pair for the whole trading period. In reality trades last only a fraction of the trading period and also positive cash flows during the trading period could produce small risk-free return. Negative cash flows take always place at the end of a trading period, not during it.[2] Hence, the return calculation still mildly underestimates returns to the strategy.

The returns are calculated for long and short positions of similar dollar amounts and the strategy is self-financing. Therefore, the return is interpreted as abnormal return. Later on I use terms return, abnormal return and excess return interchangeably when returns to the strategy, single pairs or single pairs trades are in question.

4.2.4. Analyst recommendations

In order to study the effect of divergent analyst recommendations on the returns to the statistical trading strategy I separately analyze single analyst recommendations during the trading period for all 20 pairs that are eligible for trading. From the I/B/E/S Details Recommendations database I screen all recommendations for the 40 stocks forming the 20

[2] Negative cash flow during trading period may occur in a special case of a delisting of a stock in an open pair that results in a loss to the trade.

pairs for a period starting one month prior the beginning of the trading period up to the end of the trading period, a period of 7 months. Since a pair can be opened immediately at the beginning of the trading period, it is important to know the recommendations that have been announced immediately prior to trading. Therefore, I collect recommendations also one month prior to trading.

Yu (2011) trades pairs of stocks that *the same analyst on the exact same date* gives divergent recommendations to. She uses divergent recommendations sell-hold, hold-buy and sell-buy. Strong sell and strong buy recommendations are included in sell and buy categories. An analyst is likely to follow fairly similar stocks, e.g. stocks in the same industry, and hence the stocks should be a good fit for pairs trading. Additionally, an analyst has only one macroeconomic and stock market view at a time. If recommendations for properly similar stocks diverge, it has to be because of idiosyncratic factors, not due to differences in macroeconomic or stock market views. Because similar stocks have similar market exposure, a pairs trade is market neutral.

Since I analyze only 20 pairs for divergent analyst recommendations, not a whole market universe of stocks, I have to relax some of the constraints in the methodology by Yu (2011). I evaluate whether divergent recommendations are connected with the return to a statistical pairs trade. A statistical trade that is connected to divergent analyst recommendations is a trade that immediately prior or during the trade has earned opposing recommendations to the stocks from a single analyst. Recommendations do not have to be given on the same date or on the date the trade is opened, but a pair has to be issued divergent recommendations from a single analyst before or during the open trade in order for the divergent recommendations to have an effect on the return. If a trade is executed in the same direction as the divergent recommendations, i.e. the relatively favorably recommended stock is bought and the relatively unfavorably recommended stock is sold short, I call it *according* or *accordingly to recommendations* and if a trade is executed vice versa to an according to recommendations trade, i.e. the stock that is issued relatively favorable recommendation is shorted and the stock issued relatively unfavorable recommendation is bought, I call the trade as executed *contrariwise* or *contrarily to recommendations*.

As opposed to Yu (2011) I separate buy (sell) and strong buy (strong sell) recommendations as divergent recommendations. Brav and Lehavy (2003) find significant differences in abnormal returns to recommendation changes from hold to buy and from hold to strong buy. Hence, separating buy (sell) and strong buy (strong sell) recommendations can reveal more information in recommendations.

My measure relaxes some issues of the divergent analyst recommendations methodology described by Yu (2011) in order to be applicable to a smaller set of stocks with predetermined pairs. The measure still captures all essential economic factors in the methodology. Only recommendations from same analysts are used to include the market neutrality aspect. Even though the divergent recommendations are not given on the same exact date, they are still given during a relatively short window, and as noted in Elton et al. (1986), Womack (1996) and Jegadeesh et al. (2004) the stock price drift after recommendation announcements is likely to affect the returns for up to 6 months after the announcement. In addition, Da and Schaumburg (2011) find that reaction to analysts' target price announcements does not need to be exactly on the date of the announcement to benefit from the information. Practically my measure is credible since often new recommendations follow earnings announcements which are not likely to be given on the same date by two companies in a pair, but they are likely to be given during a relatively short period, since most companies have the calendar year as their financial year and quarterly reporting is close to simultaneous. The information analysts obtain from these announcements are vital for the recommendations and making inter-company differences between companies in the same industry. My measure captures the relevant theoretical and practical issues for the study.

5. Empirical results

This section presents the empirical findings of the study. Conclusions to proposed hypotheses and links to existing literature are provided. Results of statistical pairs trading are presented first followed by analysis on analyst recommendations and linking divergent recommendations to statistical trading.

5.1. Statistical pairs trading

Table 2 reports descriptive results for the statistical trading. The results support the previous findings by Gatev et al. (2006) and Do and Faff (2010) and conclude that the statistical pairs trading strategy created by Gatev et al. (1999) is still profitable. The 6-month excess return to the strategy is 0.75% statistically significant at the 10% level. I accept H_1 at the 10% significance level that statistical pairs trading produces positive abnormal returns.

Median return to the strategy is 0.97% which is higher than the mean return. In the strategy the maximum return a trade can yield is limited whereas stop-loss rules are not employed and minimum return is not limited. The highest return to a trade in the sample is 14.7% and the minimum -28.7%. The asymmetry translates into smaller mean return compared to the median which is present throughout the results especially in Tables 6-11 where single trades are studied.

Average return to a pair generating positive return is 5.35% and to a pair generating negative return -5.40%. 40.75% of all pairs produce negative return, 55% positive return and 4.25% do not deviate enough for trading during the trading period. Average return to a single positive trade is 3.59% and to a negative trade -4.80% (not reported). The results reflect the structure of the trading where a pair can only be traded once if the first trade is negative, but multiple times if the trades are positive. Therefore the average return to a positive return pair is higher than average return to a positive return trade.

Pairs are strongly correlated in the formation period, but the relationship partly breaks in the trading period. Mean correlation in the formation period is 0.85. Correlation in the trading period is lower mean being 0.57. Sum of squared deviations is an effective pairs formation method also from correlation point of view as the mean correlation of all potential pairs in formation period is 0.40 which is 0.45 lower than the mean of selected top 20 pairs. The top pairs chosen do exhibit some persistence in correlation as the trading period mean is 0.57 which is 0.21 above the mean correlation of all potential pairs in trading period of 0.36. Hence, the matching method is efficient also when examining correlations. Formation period

Table 2

Descriptive statistics for statistical pairs trading

Table 2 shows descriptive statistics for the statistical trading strategy. First three columns report results for trading periods and next four columns for individual pairs. t-statistic shows the level of significance at which the mean return is different from zero. Correlations are between the returns of stocks forming a pair for the top 20 pairs.

	Periods			Pairs			
	All	Positive return	Negative return	All	Positive return	Negative return	Zero-trade
Number of periods / pairs	20	15	5	400	220	163	17
% of all observations	100 %	75 %	25 %	100 %	55.0 %	40.8 %	4.3 %
Return							
Mean	0.75 %	1.67 %	-2.00 %	0.74 %	5.35 %	-5.40 %	na.
Median	1.0 %	1.2 %	-2.0 %	0.8 %	4.0 %	-4.4 %	na.
Maximum	5.7 %	5.7 %	-1.1 %	37.6 %	37.6 %	-0.04 %	na.
Minimum	-3.0 %	0.3 %	-3.0 %	-25.5 %	0.03 %	-25.5 %	na.
Standard deviation	2.0 %	1.4 %	0.8 %	7.1 %	5.0 %	4.9 %	na.
t-statistic	1.64 *	na.	na.	2.08 **	na.	na.	na.
Number of traded pairs							
Mean	19.2	19.3	18.8	na.	na.	na.	na.
Median	20	19	20	na.	na.	na.	na.
Maximum	20	20	20	na.	na.	na.	na.
Minimum	16	18	16	na.	na.	na.	na.
Standard deviation	1.1	0.8	1.8	na.	na.	na.	na.
Number of roundtrip trades							
Mean	30.6	32.5	24.8	1.5	2.0	1.1	na.
Median	29	32	26	1	2	1	na.
Maximum	61	61	34	10	10	4	na.
Minimum	17	24	17	0	1	1	na.
Standard deviation	8.9	8.8	6.9	1.0	1.2	0.4	na.
Pairwise return correlation in formation period							
Mean	na.	na.	na.	0.85	0.86	0.84	0.81
Median	na.	na.	na.	0.89	0.90	0.89	0.87
Maximum	na.	na.	na.	0.99	0.99	0.99	0.96
Minimum	na.	na.	na.	-0.61	-0.61	0.28	0.16
Standard deviation	na.	na.	na.	0.15	0.15	0.14	0.21
Pairwise return correlation in trading period							
Mean	na.	na.	na.	0.57	0.62	0.49	0.79
Median	na.	na.	na.	0.72	0.75	0.67	0.89
Maximum	na.	na.	na.	0.98	0.98	0.96	0.97
Minimum	na.	na.	na.	-0.83	-0.71	-0.83	0.00
Standard deviation	na.	na.	na.	0.38	0.35	0.41	0.26

** Statistically significant at the 5% level; * Statistically significant at the 10% level correlations are not materially different between pairs that yield positive return and pairs that yield negative return.

Lower correlation during trading period enables large enough deviations to make profitable trades. In fact, it can even be necessary for trading. In my sample zero-trade pairs show as strong correlation during trading period as during formation period. Keeping in mind that the method for pairs matching is not correlation, but sum of squared deviations, the correlations during formation period are very strong. In a volatile sideways market without a descending or ascending trend the correlation between a pair can be large and negative when the stock series frequently cross and produce a low sum of squared deviations. These cases decrease the mean correlation. When the deviations are high enough, but not too high, these pairs produce the best trading results. In my sample zero-trade pairs never have negative correlations.

In Table 3 I report trading results divided into trading periods. Differences in characteristics between trading periods with positive and trading periods with negative returns are small. Mean number of roundtrip trades is higher for positive return periods (32.5) than for negative return periods (24.8). This is an intuitive result, because the number of negative return trades for each period is limited to 20, whereas the number of positive trades does not have a limit. Naturally a higher number of trades imply that the increase in trades is mainly from the increase in positive trades. The numbers of positive and negative trades confirm that the higher number of trades for positive return periods is in fact due to increase in positive return trades, not due to decrease in negative return trades.

Major difference between negative and positive return trading periods is return during formation period. Return all sample stocks during formation period is 10.3 %-points higher for trading periods with positive return (14.6%) than for trading periods with negative return (4.3%). Single extreme observations do not explain the difference. One plausible explanation could be that pairs that are formed during an up market are formed on the basis of fundamentals and thus have a strong relationship, whereas pairs formed in down market do not follow fundamentals as strictly. Karlsson, Loewenstein and Seppi (2009) find that

Table 3

Descriptive statistics for statistical pairs trading by trading periods

Table 3 shows results of the statistical trading divided into trading periods for the whole sample period from year 2000 to 2010. Notation 1/2001 denotes trading period that lasts for the first half of year 2001 and notation 2/2001 denotes trading period that lasts for the second half of year 2001, etc. Columns 1-3 report results for the statistical trading. Columns 4-7 report results for all sample stocks during formation and trading periods. Last two columns report mean correlations between returns to two stocks that form a pair in the top 20 pairs.

	Pairs trading return	Number of traded pairs	Number of roundtrip trades	Mean formation period return for sample stocks	Mean formation period volatility for sample stocks	Mean trading period return for sample stocks	Mean trading period volatility for sample stocks	Pairwise correlation on formation period	Pairwise correlation on trading period
1/2001	2.56 %	20	35	44.3 %	41.5 %	9.0 %	26.8 %	0.83	0.26
2/2001	2.82 %	19	29	39.8 %	38.6 %	-3.3 %	23.9 %	0.83	0.38
1/2002	-2.99 %	18	19	2.3 %	38.7 %	-2.1 %	22.9 %	0.67	0.49
2/2002	2.73 %	19	35	-3.0 %	33.8 %	-13.8 %	41.9 %	0.82	0.51
1/2003	1.22 %	19	26	-10.7 %	47.2 %	18.7 %	24.3 %	0.78	0.75
2/2003	1.76 %	18	29	-0.2 %	47.4 %	15.5 %	20.0 %	0.84	0.48
1/2004	0.30 %	20	24	38.1 %	29.5 %	4.3 %	15.4 %	0.94	0.47
2/2004	1.77 %	18	35	20.3 %	24.7 %	14.6 %	16.5 %	0.88	0.80
1/2005	-1.13 %	20	28	20.3 %	23.3 %	11.9 %	16.7 %	0.89	0.73
2/2005	1.12 %	19	34	28.9 %	23.9 %	0.6 %	18.7 %	0.91	0.59
1/2006	-2.59 %	20	26	13.7 %	25.6 %	8.8 %	17.3 %	0.88	0.14
2/2006	0.99 %	20	32	11.7 %	25.9 %	15.4 %	13.9 %	0.81	0.78
1/2007	0.95 %	20	32	25.5 %	22.3 %	5.3 %	16.0 %	0.92	0.63
2/2007	0.92 %	20	35	21.4 %	22.4 %	2.7 %	22.6 %	0.89	0.47
1/2008	-1.97 %	20	34	8.3 %	27.9 %	-4.8 %	23.0 %	0.84	0.66
2/2008	5.66 %	20	61	-0.9 %	31.0 %	-20.2 %	48.2 %	0.81	0.70
1/2009	1.51 %	20	29	-24.3 %	51.9 %	-0.2 %	32.3 %	0.87	0.63
2/2009	-1.34 %	16	17	-23.1 %	60.0 %	16.8 %	21.6 %	0.90	0.65
1/2010	0.31 %	18	24	16.9 %	39.2 %	-4.8 %	20.5 %	0.89	0.63
2/2010	0.43 %	19	28	11.2 %	28.3 %	17.9 %	17.0 %	0.80	0.71

Continued

Table 3 (continued)

Descriptive statistics for statistical pairs trading by trading periods

	Pairs trading return	Number of traded pairs	Number of roundtrip trades	Mean formation period return for sample stocks	Mean formation period volatility for sample stocks	Mean trading period return for sample stocks	Mean trading period volatility for sample stocks	Pairwise correlation on formation period	Pairwise correlation on trading period
Mean	0.75 %	19.2	30.6	12.0 %	34.1 %	4.6 %	23.0 %	0.85	0.57
Median	0.97 %	20	29	12.7 %	30.2 %	4.8 %	21.1 %	0.85	0.63
Standard deviation	2.05 %	1.1	8.9	19.1 %	11.0 %	10.8 %	8.8 %	0.06	0.17
Correlation with trading return	na.	0.19	0.74	0.10	0.04	-0.34	0.59	0.04	0.13

investors are not as attentive in down market and hence stock price movement does not follow fundamentals as strictly as in up market. This observation is reflected in the formed pairs.

The explanation would require that the trading period is also an up market period and stocks would be traded according to their fundamentals, not in panic in down market when the fundamentals do not perhaps matter as much as in up market. However, the mean return for trading periods where both formation and trading are up market periods is lower (0.53%) than for other periods (0.98%). A counter argument would be that in up market trading periods investors are well aware of the fundamental relationships between stocks and do not let a pair diverge enough for profitable pairs trading.The correlation between pairs trading returns and general market volatility during trading period is positive 0.60 indicating that higher volatility generates more profitable divergence-convergence opportunities for pairs trading. Mean return to trading periods when volatility during formation is below (above) average and during trading above (below) average is 2.16% (-0.56%) indicating that when pairs are formed in low volatility environment, the two standard deviation trading limits are small and high volatility in trading period breaches the limits multiple times for profitable pairs trading. Vice versa, when formation volatility is high and trading volatility low, profitable opportunities for pairs trading are scarce. Returns to cases where volatility in both formation and trading period is above or below average are 2.03% and 0.31%, between the former two extremes. In general, results show that high volatility is better for pairs trading than low volatility.

5.1.1. Comparison to earlier research

I find abnormal return of 0.75% for a 6-month trading period. The excess return is lower than found by Gatev et al. (2006) for utility stocks between 1962 and 2002, 6.50%. However, the excess return is in line with the more recent study by Do and Faff (2010) who find a 6-month excess return for utilities of 1.08% during 2003-2008. Hence, my results support the finding that excess returns to the pairs trading strategy are smaller in more recent years. The period under study is, however, too short to provide evidence of the diminishing returns in time. The effect is small and statistically not significant.

Gatev et al. (2006) attribute diminishing returns to increased trading and hedge fund activity that compete away the excess profits. Do and Faff (2011) offer an alternative explanation that the declining returns are because of increasing amount of pairs that do not converge after divergence. My results show evidence of both effects. Figure 3 shows the proportions of positive and negative return and zero-trade pairs through all periods and mean returns to positive and negative return pairs through all periods. Average returns to positive and negative return pairs have both moved closer to zero. During the first ten trading periods mean return to positive pairs is 5.2% and to negative pairs -6.2%. During the ten last periods returns are 5.1% and -4.9%. The closing on zero for both positive and negative return pairs shows a decline in the spreads between stocks in a pair which is evidence of the effect of increased trading suggested by Gatev et al. (2006). The effect is not statistically significant, however.

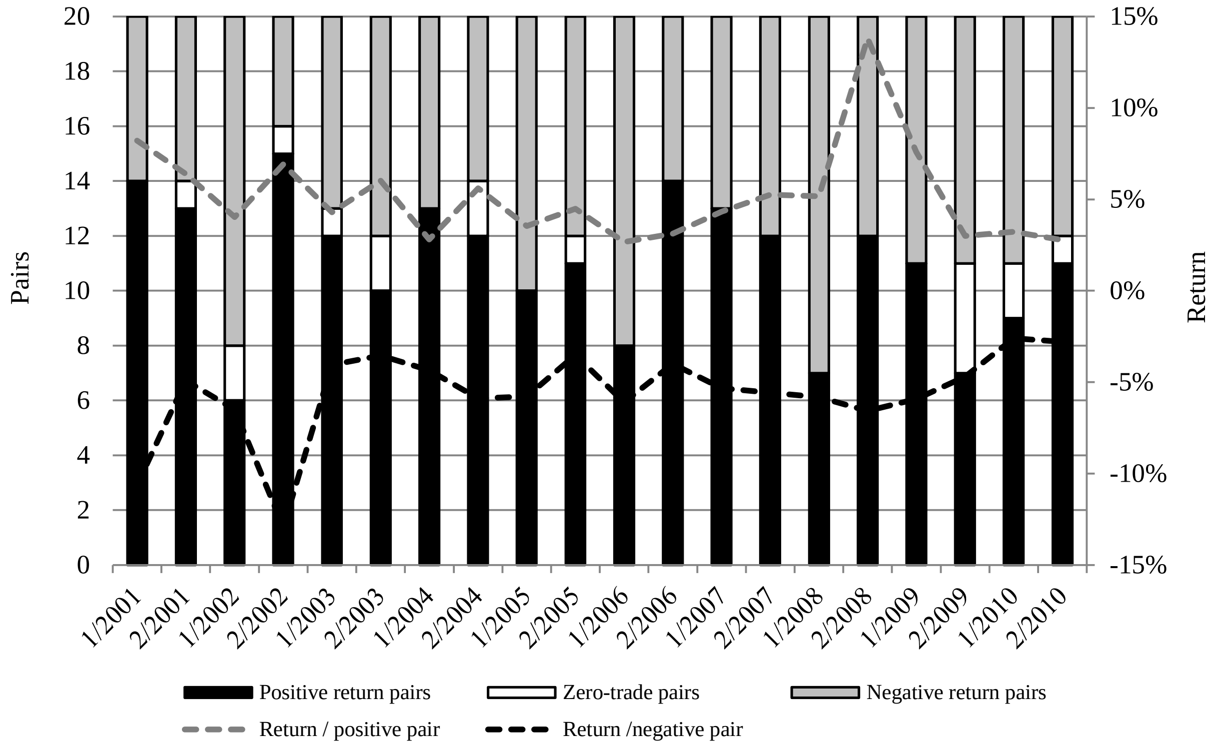
The average proportion of positive return pairs during first ten trading periods is 58.0% and proportion negative return pairs 37.0%. For last ten trading periods proportions are 52.0% positive and 44.5% negative return pairs. The change is statistically significant at the 10% level and is evidence of the increasing amount of pairs that never converge as suggested by Do and Faff (2010). Which of the effects has had more impact on the returns to the whole statistical pairs trading strategy is out of the scope of this study.

Trading returns and characteristics in my sample are very similar to earlier studies. The closest comparison can be found in a study by Do and Faff (2010) where they report trading results to top 20 pairs of utility stocks during 2003-2008. Mean and median 6-month excess returns to the strategy were 1.08% and 0.96% significant at the 1% level. My corresponding figures are 0.75% and 0.97% significant at the 10% level when examining trading periods. Portion of negative return trading periods in Do and Faff (2010) is 41% and in my study 25%. On pair level the mean 6-month excess return in Do and Faff (2010) is 1.19% and standard deviation 7.35%. My return is somewhat lower, a mean 6-month excess return of 0.74% and a standard deviation of 7.12%. Average sum of squared deviations of top 20 pairs during formation is 17% higher in my sample than in Do and Faff (2010).

Figure 3

Distribution of positive and negative returns and positive and negative return pairs by periods

Figure 3 shows on the left axis the numbers of positive return, negative return and zero-trade pairs in all 20 6-month trading periods (bars). On the right axis the figure shows mean returns to positive return and negative return pairs in all trading periods (dashed lines). Notation 1/2001 denotes trading period that lasts for the first half of year 2001 and notation 2/2001 denotes trading period that lasts for the second half of year 2001, etc.



Gatev et al. (2006) report descriptive trading results. For top 20 pairs of utility stocks during 1962-2002 portion of trading periods with negative return is 19%. For the top 20 pairs of all stocks during 1962-2002 average number of pairs that were actually traded during a 6-month trading period is 19.3 and the average number of roundtrip trades per pair is 1.96. My results are very similar. Average number of traded pairs is 19.2 and average number of roundtrip trades per pair 1.53, somewhat lower than in Gatev et al. (2002), which is also a sign about the declining profits to the strategy.

5.1.2. Transaction costs

When evaluating results from market data one needs to assess the potential effects that market frictions have on the results. In a trading strategy the effects are related to transaction costs. In a contrarian long-short strategy the specific variables are brokers' commissions, bid-ask spread and restrictions on short-selling.

Bhardwaj and Brooks (1992) estimate that brokers' commissions for a one-way transaction during 1982-1986 amount to approximately 1.41%. Jones (2002) provides a more recent estimate of 0.10% in year 2000 for NYSE listed stocks. The average number of roundtrip trades for a pair during six months in our sample is 1.53 and each roundtrip includes 4 one-way trades. Therefore brokers' commissions total 0.61% ($1.53 \cdot 4 \cdot 0.10\%$) for pair during six months of trading. Excess return after commissions to the strategy equals 0.14%. Even though the strategy is not trading intensive, the commissions swipe a large share of profits.

Bhardwaj and Brooks (1992) find an average 1.64% bid-ask spread for stocks in NYSE and AMEX. Jones (2002) estimates a spread of approximately 0.20% for Dow Jones stocks in year 2000. The spread is larger for small capitalization stocks than for large stocks as shown in Stoll and Whaley (1982) and more recently in Lesmond, Ogden and Trzcinka (1999). My sample consists of utility stocks that are larger than the average stocks and hence the bid-ask spread is likely to be smaller than average. The trading strategy I analyze demands liquidity and is therefore likely to pay the spread when trading. Moreover, the strategy is contrarian and when using closing prices the results are likely to be biased upward due to the bid-ask bounce as pointed out in Conrad and Kaul (1993) and Stoll and Whaley (1982). The strategy sells stocks that have appreciated and buys stocks that have depreciated compared to their pair. Hence the strategy is more likely to sell an absolute winner and buy an absolute loser. The closing price of the winner is more likely to be an ask price and the loser's a bid price. By using closing prices the strategy implicitly sells stocks at the higher ask price and buys stocks at the lower bid price. Since the strategy demands liquidity, in practice it is more likely to trade at the opposite prices: sell at the lower bid price and buy at the higher ask price.

Gatev et al. (2006) estimate the effect of the bid-ask bounce on the results by delaying the execution of the trades by one day. When the signal for opening a trade is observed on day t_0 the trade is opened on day t_1 and the closing of the trade is delayed similarly unless it is the last day of the trading period in which case the trade is closed on that day. Table 4 presents descriptive results for the statistical trading when the execution is delayed by one day. The excess 6-month return drops by 0.38 %-points from 0.74% to 0.36%. The excess return of 0.36% is not statistically significant. The 0.38 %-points decrease in return means a bid-ask spread of 0.06% (0.38% / (1.53 · 4)) for a one-way trade which is smaller than estimated in earlier studies. The smallest comparable bid-ask spread documented is 0.09% for stocks with a price per share of larger than 10$ in Conrad and Kaul (1993). A reliable estimate of the spread for the sample period is not available and reasons for the smaller estimated spread could be continuation in the decline in spreads or smaller than average spreads in my sample stocks because of the relatively large size.

Table 4

Descriptive statistics for statistical trading with one day delay in trade execution

Table 4 shows descriptive statistics for the statistical trading strategy when execution of trades, opening and closing, is delayed by one day with respect to the opening and closing signals. First three columns report results for trading periods and next four columns for individual pairs. t-statistic shows the level of significance at which the mean return is different from zero.

	Periods			Pairs			
	All	Positive return	Negative return	All	Positive return	Negative return	Zero-trade
Sample	20	15	5	400	215	168	17
% of all observations	100 %	75 %	25 %	100 %	55.0 %	40.8 %	4.3 %
Return							
Mean	0.36 %	1.14 %	-1.96 %	0.36 %	4.87 %	-5.38 %	na.
Median	0.67 %	1.01 %	-1.83 %	0.47 %	3.75 %	-4.20 %	na.
Standard deviation	1.66 %	1.00 %	0.68 %	6.80 %	4.52 %	4.99 %	na.
t-statistic	0.99	na.	na.	1.06	na.	na.	na.

Gatev et al. (2006) find that 6-month excess return to the strategy drops by 3.25 %-points when the execution of the trades is delayed by one day. Do and Faff (2010) execute the same analysis and find a drop in 6-month excess return of 2.40 %-points. The estimate of spread in my sample is smaller than in either of the two earlier studies which I attribute to the differences in sample periods. My sample spans from 2000 to 2010 whereas Gatev et al. (2006) and Do and Faff (2010) use a sample starting from 1962. Bid-ask spreads in earlier years were significantly larger than in my sample as illustrated in Jones (2002). Da and Schaumburg (2011) note that decimalization in NYSE and NASDAQ in 2001, the first year of trading in my sample, increased liquidity and reduced most trading costs significantly.

D'Avolio (2002) studies the characteristics of U.S. short-selling markets between years 2000 and 2001. He finds that 16% of stocks in CRSP database are impossible to borrow, but these stocks comprise only less than 0.6% of total market value meaning that the stocks are generally very small and illiquid. Hence, the constraint is not likely to affect my results. The borrowing cost for 91% of stocks is on average 0.17% per annum and the rest of the stocks are so called market specials with higher borrowing costs. The probability of being a market special decreases with size and institutional holding which are both high for my sample of utility stocks. The average time a trade is open is also short and hence the total costs of short-selling are very small, less than 0.06% for six months.

Examining the transaction costs reveals that the strategy would not survive all transaction costs. Brokers' commissions are high compared to returns and return after allowing for bid-ask spread is not statistically significant. Short-selling costs are only a minor addition to the costs of the whole trading strategy. The results raise same question that Gatev et al. (2006) already asked about trading too small deviations not allowing for the transaction costs even if the trade is successful. One fact biasing return downwards is excessive trading that takes place when a trade is opened at the very end of a trading period not allowing enough time for the stocks to converge. Reason why Gatev et al. (2006) and Do and Faff (2010) find the strategy profitable even after accounting for transaction costs is that the strategy itself was more profitable in earlier years, whereas my sample covers only a recent period when the returns have already mostly diminished.

5.2. Analyst recommendations

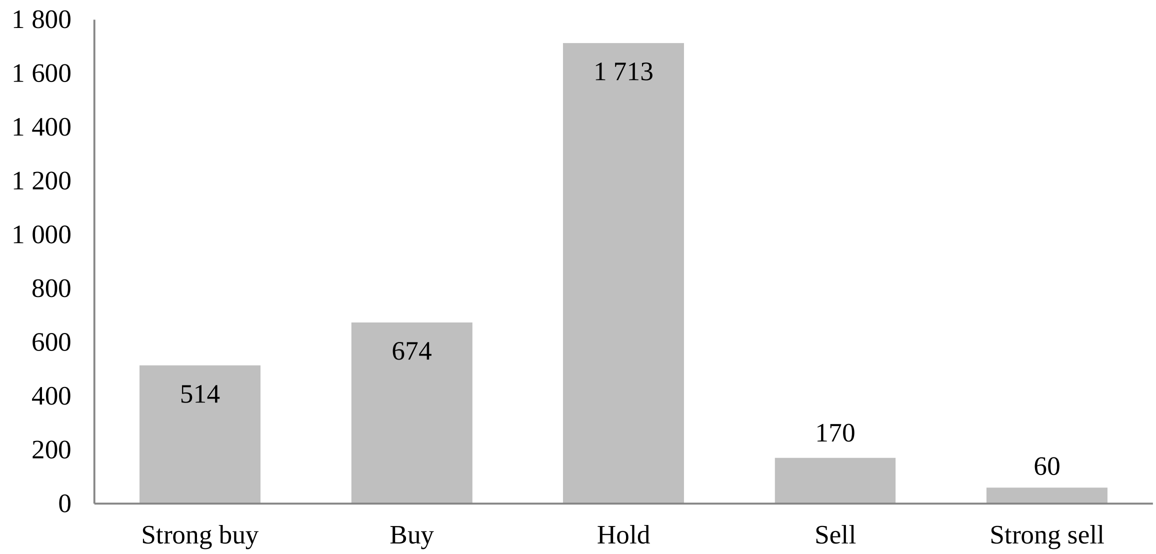
5.2.1. Distribution of recommendations

The distribution of analyst recommendations is skewed towards buy and strong buy recommendations and has a large mass on hold recommendations. Figure 4 presents distribution of the recommendations. The distribution is in line with earlier studies' observations and analysts' bias to issue buy recommendations. For example Elton et al. (1986), Barber et al. (2001) and Brav and Lehavy (2003) report similar distributions. 55% are hold recommendations, 38% buy or strong buy and 7% sell or strong sell recommendations. The numerical scale of recommendations in I/B/E/S is reversed strong buy obtaining the smallest value and strong sell largest. Strong buy recommendations are given a value of 1, buy value of 2, hold value of 3, sell value of 4 and strong sell recommendations a value of 5.

Figure 4

Distribution of recommendations

Figure 4 shows the distribution of recommendations. Left axis shows the number of recommendations in each category. In the analysis strong buy corresponds to value 1, buy to value 2, hold to value 3, sell to value 4 and strong sell to value 5.



Mean of all recommendations in my sample is 2.55 and mean recommendation for trading period is higher than 3 only once in the 20 periods. Boni and Womack (2006) report mean consensus rating for all stocks of close to 2. Left skewed distribution characterizes aptly the positive bias in analyst recommendations.

5.2.2. Investment value in analyst recommendations

To study analysts' recommendation accuracy I compare consensus trading period recommendations to each stock with the stocks return during the period. I test analysts' abilities to distinguish between stocks that perform better than average versus those that perform worse than average. Relative recommendation ability I test with consensus recommendations between stocks in pairs formed in statistical trading.

The data contains a total of 3 126 recommendations for 40 utility stocks for 20 trading periods on a total of 10 years period. The average number of recommendations issued for a stock during 7-months starting one month prior to trading is 3.9. My default assumption in analyzing divergent recommendations is that analysts' relative recommendations are accurate.

Table 5 shows the statistics for correct level and relative recommendations. First column shows the proportion of correct recommendations for period when the benchmark is the mean return of sample stocks during the trading period. Buy (Sell) consensus recommendations on stocks that return above (below) the sample mean are considered correct. The consensus recommendation is defined as buy (sell) when the mean recommendation is a value below (above) 3. I eliminate consensus recommendations that take the value of exactly 3 corresponding to a hold recommendation. The meaning and correctness of hold recommendations is not unequivocal.

Mean proportion of correct level recommendations is 52.8%. The proportion is above 50% at the 10% statistical significance level. Hence, it seems that analysts have a weak ability to issue correct recommendations within an industry. The marginally above 50% rate of correct

Table 5

Percentages of correct level and relative recommendations

Table 5 shows statistics for correct recommendations on trading periods. Proportions in the first column are calculated from consensus recommendations that can be identified as buy (mean recommendation below value 3) or sell (mean recommendation above value 3). Proportions in the second column are calculated from top 20 pairs that have differing mean recommendations for the stocks. First column shows the results when a buy (sell) recommendation is considered correct, if the return to stock is above (below) the period's mean return calculated from all sample stocks. Second column shows the results when a recommendation is considered correct, if the stock that has the relatively more favorable recommendation in a pair earns higher return. t-statistic shows the level of significance at which the mean proportion of correct recommendations is different from 50%.

	Correct level recommendation compared to period mean return	Correct relative recommendation between pair
Number of stocks / pairs	540	278
Proportion correct recommendations		
Mean	52.8 %	58.8 %
Median	54.8 %	57.7 %
Standard deviation	8.0 %	14.5 %
t-statistic (≠ 50%)	1.55 *	2.72 ***

*** Statistically significant at the 1% level; * Statistically significant at the 10% level

recommendations does not seem to be economically satisfactory for an analyst, however. Furthermore, the correlation between consensus recommendations and stock returns (not reported) are very small indicating that analysts' consensus level recommendations, even though correct on average on a two point buy/sell scale, are not particularly accurate throughout the whole recommendation scale of 1 through 5.

More important than the results of level recommendations to my study is the performance of analysts' relative recommendations between a pair of stocks. Second column in Table 5 shows the results for analysts' relative recommendations for a pair. Pairs are the ones formed in statistical pairs trading and the relative recommendations are evaluated only within a pair. If the stock in a pair that has the higher return has relatively more favorable consensus recommendation, the relative recommendation is correct. The mean proportion of correct relative recommendations is 58.8%. The proportion is higher than 50% at the 1% statistical significance level. I accept hypothesis H_2 that analysts' relative recommendations have investment value.

Interestingly, analysts on average are better in picking a relative winner between a close pair of stocks than within an industry. The relative recommendations between a close peer are more informative than a comparison of recommendations within an industry which is often the case when analysts employ relative multiples-based valuation techniques. Correlation between difference in recommendations and difference in returns between stocks in a pair is -0.15, however. The magnitude of the difference in consensus recommendations is not correlated with the magnitude of return difference. Though the relative recommendations are correct on average, the magnitude of the difference in returns cannot be inferred from the magnitude of the difference in recommendations. The finding is not completely in line with Brav and Lehavy (2003) who show that the magnitude of change in recommendations is informative. One explanation is that the stocks in a pair are really close substitutes, because of which it is difficult for an analyst to give widely differing recommendations.

Results show that on consensus level analysts have a weak ability to recommend winner stocks within an industry. Between two statistically close stocks analysts recommendation ability is, however, significantly better. Results about positive abnormal return to pairs trading and analysts' significant ability to recommend the relative winner in a statistical pair underline the importance of the joint study.

5.3. Divergent recommendations in pairs trading

The finding that analysts do well in relative recommendations between a statistical pair advocates research on connections between pairwise relative recommendations and statistical pairs trading. Next I analyze this relationship between divergent recommendations and statistical pairs trading. While in the previous section relative recommendations were analyzed on consensus level, in this section divergent recommendations are by definition relative differing recommendations issued by a *single* analyst.

Table 6 sums the effect that divergent recommendations have on pairs trading. Of all 612 trades 112 are connected to divergent recommendations. Trades connected to divergent recommendations are trades that are issued divergent recommendations before or during the trade as defined in section 4.2.4. Mean return to trades connected to divergent recommendations is -1.09% significant at the 5% level. Mean return to the 500 trades not connected to divergent recommendations is 0.85% significant at the 1% level. In aggregate divergent recommendations weaken the return to statistical pairs trading. The return of -1.09% is significantly different from the mean return to all trades of 0.49% at the 1% level. Proportion of negative return trades is much higher in trades connected to divergent recommendations than in trades not connected to divergent recommendations.

Table 6

Returns to trades by connection to divergent recommendations

Table 6 shows return statistics for all trades in the first column, for trades that are connected to divergent recommendations in the second column and for trades that are not connected to divergent recommendations in the third column. Trades connected to divergent recommendations are trades that are issued divergent recommendations before or during the trade. t-statistics for mean returns are shown compared to 0% return and compared to the mean return to all trades of 0.49%.

	All trades	Trades connected to divergent recommendations	Trades not connected to divergent recommendations
Number of trades	612	112	500
% of all trades	100 %	18 %	82 %
Return			
Mean	0.49 %	-1.09 %	0.85 %
Median	1.97 %	-0.07 %	2.17 %
Standard deviation	5.38 %	6.42 %	5.06 %
t-statistic (≠ 0%)	2.26 **	-1.79 **	3.74 ***
t-statistic (≠ 0.49%)	na.	-2.60 ***	1.56 *
Number of positive return trades	386	55	331
% of observations	63 %	49 %	66 %
Number of negative return trades	226	57	169
% of observations	37 %	51 %	34 %

*** Statistically significant at the 1% level; ** Statistically significant at the 5% level; * Statistically significant at the 10% level

Rather than keeping relative prices in line, divergent recommendations, whether the cause or effect, are a sign of the relationship in pairs breaking up. Relationships hold best in pairs that do not have divergent recommendations disturbing the markets. Divergent recommendations could be a sign of fundamental changes in the companies to which analysts react to. In that case the relationship is correctly broken up and contrarily in the lack of divergent recommendations the estimated relationship holds creating opportunities for lucrative pairs trading. This reasoning is in line with Papadakis and Wysocki (2008) who find that pairs trades opened after earnings announcements or analysts' forecasts are less profitable than other trades.

Negative return to trades connected to divergent recommendations as such does not guide to shirk or trace divergent recommendations. As H_3 states, the negative returns to trades connected to divergent recommendations could be caused by a majority of trades where divergent recommendations are issued before the opening of the trade and trades where divergent recommendations are issued after the opening of the trade, but the statistical trade is executed contrariwise to the recommendations. In this case trades, where divergent recommendations contribute to the closing of the spread between two stocks, would account only for a small proportion of trades. In analyzing the accuracy or benefits of divergent recommendations we have to look at the timing of the recommendations as well as the execution of statistical pairs trades.

5.3.1. Returns to trades connected to divergent recommendations

Table 7 shows returns to trades connected to divergent recommendations divided by timing of recommendations and execution of trade. The proportions of trades where recommendations are issued before trade opening and after trade opening are close to equal. Also proportions of trades executed accordingly to recommendations and contrariwise to recommendations are equal. Mean return to trades in all four categories are negative.

Mean return to trades where recommendations are issued before the opening of the trade is -0.53%. The return is not statistically significant. Insignificant negative return is an indication that after analysts issue divergent recommendations the spread between the pair widens up to the point where it reaches the limit to open a pairs trade. After the trade is opened the spread soon arrives at a new equilibrium state after which it stays stagnant. The chain of events leads to opening of pairs traded when the spread is still widening. The change is not temporary and thus returns to pairs trades are slightly negative. This inference is in line with studies by

Table 7

Returns to trades connected to divergent recommendations by timing of recommendations and execution of trades

Table 7 shows return statistics for trades that are connected to divergent recommendations. First column shows returns to all trades, second and third columns to trades where divergent recommendations are issued before and after opening of the trade and fourth and fifth columns to trades that are executed accordingly and contrariwise to recommendations. t-statistics for mean returns are shown compared to 0% return and compared to the mean return to all trades of 0.49%.

	Trades connected to divergent recommendations	Trades where recommendations issued before trade opening	Trades where recommendations issued after trade opening	Trades executed accordingly to recommendations	Trades executed contrariwise to recommendations
Number of trades	112	57	55	54	58
% of all trades	100 %	51 %	49 %	48 %	52 %
Return					
Mean	-1.09 %	-0.53 %	-1.66 %	-0.48 %	-1.65 %
Median	-0.07 %	-0.05 %	-0.23 %	0.65 %	-0.37 %
Standard deviation	6.42 %	6.53 %	6.31 %	6.12 %	6.69 %
t-statistic ($\neq$ 0%)	-1.79 **	-0.62	-1.95 **	-0.58	-1.88 **
t-statistic ($\neq$ 0.49%)	-2.60 ***	-1.19	-2.53 ***	-1.17	-2.44 ***
Number of positive return trades	55	28	27	30	25
% of observations	49 %	49 %	49 %	56 %	43 %
Number of negative return trades	57	29	28	24	33
% of observations	51 %	51 %	51 %	44 %	57 %
Number of trades executed accordingly to recommendations	54	23	31	na.	na.
% of observations	48 %	40 %	56 %	na.	na.
Number of trades executed contrariwise to recommendations	58	34	24	na.	na.
% of observations	52 %	60 %	44 %	na.	na.

*** Statistically significant at the 1% level; ** Statistically significant at the 5% level

Continued

Table 7 (continued)

Returns to trades connected to divergent recommendations by timing of recommendations and execution of trades

	Trades connected to divergent recommendations	Trades where recommendations issued before trade opening	Trades where recommendations issued after trade opening	Trades executed accordingly to recommendations	Trades executed contrariwise to recommendations
Number of trades with recommendations issued before trade opening	57	na.	na.	23	34
% of observations	51 %	na.	na.	43 %	59 %
Number of trades with recommendations issued after trade opening	55	na.	na.	31	24
% of observations	49 %	na.	na.	57 %	41 %

*** Statistically significant at the 1% level; ** Statistically significant at the 5% level

Womack (1996) and Jegadeesh et al. (2004) that stock price drift after new recommendations lasts for one to six months. 60% of trades are executed contrariwise to recommendations which advocates that the spread in fact widens to the direction that the recommendations indicate. Papadakis and Wysocki (2008) find contradictory results that analysts issue recommendations contrary to past returns and thus accelerate convergence of pairs.

Return to trades where recommendations are issued after trade opening is -1.66% significant at the 5% level. Trades where recommendations are issued after trade opening contribute more to the aggregate negative return than trades where recommendations are issued before trade opening. The finding is unexpected since a majority of 56% of the trades are executed accordingly to recommendations. If the spread drifts according to recommendations, these trades yield positive returns when the recommendations cause the spread to narrow. Theoretical explanation is that, because negative return to a trade is not limited, but positive return is, the 44% of trades executed contrariwise to recommendations yield highly negative returns that outweigh the positive returns to the majority of trades executed accordingly to recommendations. Proportion of trades yielding positive returns is 49% against the proportion of 56% of trades that are executed accordingly to recommendations. Hence, at least some trades executed according to recommendations yield negative returns. This motivates an alternative explanation that the spread does not drift the way recommendations indicate, but it moves to the opposite direction causing negative returns to trades executed according to recommendations. The alternative explanation contradicts with theory and findings about post-recommendation drift.

The distribution and returns to trades executed accordingly and contrariwise to recommendations are also interesting. Mean return to trades executed accordingly to recommendations is -0.48%. The return is not statistically significant. Mean return to trades executed contrariwise to recommendations is -1.65% which is significant at the 5% level. Trades executed contrariwise contribute more to the aggregate negative return than trades executed accordingly to recommendations. 59% of contrariwise executed trades are trades with recommendations issued before trade opening. Furthermore, 57% of trades yield negative returns. This observation strengthens the note that the spread opens in the direction recommendations indicate and continues to widen after a pairs trade is opened.

The results indicate that the largest contributor to the negative return are trades executed contrariwise to recommendations with recommendations issued after the opening of the trade. As discussed, however, there are various other possible explanations for the negative returns. A study about the distribution of accordingly and contrariwise executed trades in trades with recommendations issued before and after trade opening shows that the largest contributor is indeed contrariwise executed trades where recommendations are issued after trade opening. The effect from other trades is not unambiguous, however.

5.3.2. Timing of recommendations and post-recommendations drift

In trades where recommendations are issued before trade opening trades executed accordingly to recommendations yield a mean return of 0.00% and trades executed contrariwise yield a return of -0.89%. Neither of the returns is statistically significant. Table 8 shows returns to trades where recommendations are issued before trade opening divided into accordingly and contrariwise executed trades.

Negative return to trades executed contrariwise reinforces the hypothesis that spread opens in the direction of recommendations and the drift continues slightly also after trade opening. Since the negative return is not statistically significant it seems that pairs reach a new equilibrium state close to the trigger point of opening trade and thus the spread moves only slightly after trade opening.

The relatively high proportion of trades executed accordingly to recommendations is contradictory to the expected post-recommendations drift. In these trades between issue of recommendations and trade opening the spread moves in the opposite direction than the recommendations indicate. Mean return to trades is zero. After the recommendations the pair diverges to the opposite direction than recommendations indicate and reaches a new equilibrium at the opening of the trade, similarly as in trades executed contrariwise to recommendations.

Table 8

Returns to trades where divergent recommendations are issued before the opening of the trade by execution of trades

Table 8 shows return statistics to trades connected to divergent recommendations where recommendations are issued before the opening of the trade. First column shows returns to all trades and second and third to trades executed accordingly and contrariwise to recommendations. t-statistics for mean returns are shown compared to 0% return and compared to the mean return to all trades of 0.49%.

	Trades where recommendations issued before trade opening	Trades executed accordingly to recommendations	Trades executed contrariwise to recommendations
Number	57	23	34
% of all trades	100 %	40 %	60 %
Return			
Mean	-0.53 %	0.00 %	-0.89 %
Median	-0.05 %	1.85 %	-0.13 %
Standard deviation	6.53 %	6.60 %	6.55 %
t-statistic (≠ 0%)	-0.62	0.00	-0.80
t-statistic (≠ 0.49%)	-1.19	-0.36	-1.23
Number of positive return trades	28	12	16
% of observations	49 %	52 %	47 %
Number of negative return trades	29	11	18
% of observations	51 %	48 %	53 %

The relatively high proportion of accordingly to recommendations executed trades and the statistical insignificance of returns are contrary to the expected post-recommendations drift. Even though results about trades executed contrariwise to recommendations indicate to the right direction, they are not strong enough to accept H_{3a} that trades where recommendations are issued before the opening of the trade yield abnormal negative returns. I reject H_{3a} because of the lack of statistical significance.

Table 9 shows returns to the spread between issue of recommendations and trade opening. Mean return is -2.61% significant at the 1% level.[3] The returns are similar to trades executed accordingly and contrariwise to recommendations. The drift causes the spread to cross trade

[3] 7 observations yield positive returns between issue of recommendations and trade opening. In these observations recommendations have been issued before the beginning of the trading period or during preceding trade and therefore yield positive return. These observations are quirks due to the construction of the test, but because of low number and insignificant influence on results they have not been omitted from the study.

opening threshold on average 25 days after the issue of recommendations. In the following on average 45 days when the trade is open, the drift is dramatically smaller and statistically not significant. The post-recommendation drift occurring approximately during one month is in line with previous studies although in the shorter end of the range.

The small negative return, though insignificant, to trades where recommendations are issued before trade opening indicates that an investor is better off when not investing in pairs which spread is opened after issue of divergent recommendations. Furthermore, it does not matter whether the spread opens in the direction of recommendations or in the opposite direction. Finding is in line with Engelberg et al. (2009) and indicates that recommendations reflect firm-specific information rather than industry information and thus relative recommendations between stocks within an industry are informative.

Initial examination indicated that the largest contribution to the negative returns is from trades that are executed contrariwise to recommendations and where recommendations are issued after trade opening. Splitting trades into trades executed accordingly and contrariwise to recommendations confirms the observation. Table 10 shows returns to trades where recommendations are issued after trade opening divided into accordingly and contrariwise to recommendations executed trades. Return to trades executed accordingly is -0.84%, but not statistically significant. Return to trades executed contrariwise is -2.72% statistically significant at the 5% level.

Statistically significant negative return to trades executed contrariwise to recommendations confirms H_{3b} that trades where divergent recommendations in the direction to widen the spread are issued after the opening of the trade yield abnormal negative return. Negative return to trades executed accordingly to recommendations is opposite to H_{3c} that trades that after the opening of the trade receive divergent recommendations in the direction to close the spread yield abnormal positive return. I accept H_{3b} and reject H_{3c}.

Table 9

Post-recommendations return drifts connected to divergent recommendations in trades where divergent recommendations are issued before the opening of the trade

Table 9 shows return drifts after the issue of divergent recommendations and returns to trades in trades where divergent recommendations are issued before the opening of the trade. Drift is calculated as the return of the spread between the issue of divergent recommendations and opening of the trade. Return of the spread is calculated in the same direction that the subsequent trade is executed. Drifts and returns are shown to all trades in the first two columns, to trades executed accordingly to recommendations in the second two columns and to trades executed contrariwise to recommendations in the last two columns. The first column shows the drift and the second return to the trades. t-statistic shows the level of significance at which the mean proportion of correct recommendations is different from zero.

	Trades where recommendations issued before trade opening		Trades executed accordingly to recommendations		Trades executed contrariwise to recommendations	
	Between issue of recommendations and trade opening	Between trade opening and trade closing	Between issue of recommendations and trade opening	Between trade opening and trade closing	Between issue of recommendations and trade opening	Between trade opening and trade closing
Return						
Mean	-2.61 %	-0.53 %	-2.77 %	0.00 %	-2.77 %	-0.89 %
Median	-2.40 %	-0.05 %	-2.74 %	1.85 %	-2.29 %	-0.13 %
Standard deviation	2.83 %	6.53 %	2.56 %	6.60 %	2.78 %	6.55 %
t-statistic ($\neq 0\%$)	-6.97 ***	-0.62	-5.18 ***	0.00	-5.81 ***	-0.80
Number of positive return observations	7	28	4	12	3	16
% of observations	12 %	49 %	17 %	52 %	9 %	47 %
Number of negative return observations	50	29	19	11	31	18
% of observations	88 %	51 %	83 %	48 %	91 %	53 %
Mean duration in days	25	45	33	44	19	45

*** Statistically significant at the 1% level

Table 10

Returns to trades where divergent recommendations are issued after the opening of the trade by execution of trades

Table 10 shows return statistics to trades connected to divergent recommendations where recommendations are issued after the opening of the trade. First column shows returns to all trades and second and third to trades executed accordingly and contrariwise to recommendations. t-statistics for mean returns are shown compared to 0% return and compared to the mean return to all trades of 0.49%.

	Trades where recommendations issued after trade opening	Trades executed accordingly to recommendations	Trades executed contrariwise to recommendations
Number of trades	55	31	24
% of all trades	100 %	56 %	44 %
Return			
Mean	-1.66 %	-0.84 %	-2.72 %
Median	-0.23 %	0.59 %	-1.88 %
Standard deviation	6.31 %	5.82 %	6.87 %
t-statistic ($\neq$ 0%)	-1.95 **	-0.80	-1.94 **
t-statistic ($\neq$ 0.49%)	-2.53 ***	-1.27	-2.29 **
Number of positive return trades	27	18	9
% of observations	49 %	58 %	38 %
Number of negative return trades	28	13	15
% of observations	51 %	42 %	63 %

*** Statistically significant at the 1% level; ** Statistically significant at the 5% level

Negative return to contrariwise executed trades indicates that there is value in analyst recommendations. Contrarily, the negative, though not significant, return to accordingly executed trades signals that there is not value in recommendations. A closer study on returns to trades before the issue of recommendations and after the issue shows that analyst recommendations are in fact only a small contributor in the negative returns to trades executed contrariwise to recommendations.

Table 11 shows returns to trades where recommendations are issued after the opening of the trade. The table divides returns to trades in two parts: return between trade opening and issue of recommendations and return between issue of recommendations and trade closing. Results show that negative return between trade opening and issue of recommendations is statistically significant in both accordingly and contrariwise executed trades, but between issue of recommendations and trade closing positive return to trades executed accordingly and negative return to trades executed contrariwise are not statistically significant.

Mean return to accordingly to recommendations executed trades between trade opening and issue of recommendations is -0.89% significant at the 10% level. Mean return between issue of recommendations and trade closing is 0.08% which is not statistically significant. Analysts issue recommendations in the direction to close the spread, but the spread does not converge. Time between recommendations issue and trade closing is on average 42 days during which the post-recommendation drift should be visible according to previous results.

Return to contrariwise executed trades between trade opening and issue of recommendations is -1.99% significant at the 5% level. Return from issue of recommendations to trade closing is -0.48% which is not statistically significant. In this case analysts issue recommendations in the direction to widen the spread further. The drift follows recommendations, but it is small and statistically not significant. Time between issue of recommendations and trade closing is on average 46 days, again, enough to allow for a post-recommendation drift. Plausible explanation is a fundamental change in the pairs to which markets react faster than analysts in their recommendations. Average time between trade opening and issue of recommendations is 40 days during which the return is -1.99%. Analysts seem to react to the change in the spread. Analysts notice the widening of the spread and assume a break up in the relationship between the pair and as a result issue divergent recommendations in the same direction the spread has moved. Negative return before issue of divergent recommendations yields most of the negative return to trades executed contrariwise to recommendations. Post-recommendations drift before closing the trades is only a small factor in the total negative return.

A slight reaction to divergent recommendations by the spread is visible when return between issue of recommendations and trade closing in both accordingly and contrariwise trades is examined. In accordingly executed trades recommendations seem to constrain the diverging of the spread and in contrariwise executed trades they reinforce the diverging. However, the effect can’t be shown to be statistically significant.

Table 11

Post-recommendations return drifts connected to divergent recommendations in trades where divergent recommendations are issued after the opening of the trade

Table 11 shows returns to trades before the issue of divergent recommendations and return drift after the issue of divergent recommendations in trades where divergent recommendations are issued after the opening of the trade. Return is calculated between the opening of the trade and issue of divergent recommendations. Drift is calculated as the return of the spread between the issue of divergent recommendations and closing of the trade. Return of the spread is calculated in the same direction that the trade is executed. Returns and drifts are shown to all trades in the first two columns, to trades executed accordingly to recommendations in the second two columns and to trades executed contrariwise to recommendations in the last two columns. The first column shows the return between opening of trade and issue of divergent recommendations and the second drift between issue of divergent recommendations and closing of trade. t-statistic shows the level of significance at which the mean proportion of correct recommendations is different from zero.

	Trades where recommendations issued after trade opening		Trades executed accordingly to recommendations		Trades executed contrariwise to recommendations	
	Between trade opening and issue of recommendations	Between issue of recommendations and trade closing	Between trade opening and issue of recommendations	Between issue of recommendations and trade closing	Between trade opening and issue of recommendations	Between issue of recommendations and trade closing
Return						
Mean	-1.37 %	-0.16 %	-0.89 %	0.08 %	-1.99 %	-0.48 %
Median	-0.35 %	0.48 %	-0.11 %	0.61 %	-0.58 %	0.20 %
Standard deviation	3.94 %	4.91 %	2.95 %	5.64 %	4.93 %	3.86 %
t-statistic (≠ 0%)	-2.58 ***	-0.25	-1.67 *	0.08	-1.98 **	-0.61
Number of positive return observations	22	31	14	18	8	13
% of observations	40 %	56 %	45 %	58 %	33 %	54 %
Number of negative return observations	33	24	17	13	16	11
% of observations	60 %	44 %	55 %	42 %	67 %	46 %
Mean duration in days	33	44	27	42	40	46

*** Statistically significant at the 1% level; ** Statistically significant at the 5% level; * Statistically significant at the 10% level

Even though accepting H_{3b} the conclusions about divergent recommendations are not expected. Recommendations are not the main driver of the return. Post-recommendation drift contributes less than one fifth of the negative return to contrariwise executed trades where recommendations are issued after trade opening. Moreover, the return between issue of recommendations and trade closing is statistically not significant. Hence, H_{3b} is not accepted based on the reasons hypothesized, but due to other unexplained factors.

5.3.3. Aggregate impact of divergent recommendations and implications on pairs trading

Post-recommendation drift, which is a prerequisite for my hypotheses, is not significant in divergent recommendations. In trades where recommendations are issued after trade opening the drift is small and not statistically significant. In trades executed contrariwise to recommendations and recommendations are issued before trade opening the drift is according to recommendations and significant at the 1% level, but in trades executed according to recommendations the drift is opposite to recommendations and significant at the 1% level. Hence, on aggregate the drift does not evidence any dependence on divergent recommendations.

Since divergent recommendations do not produce post-recommendation drift, the cause for statistically significant negative return to trades connected with divergent recommendations is not trades executed contrariwise to recommendations. In trades where recommendations are issued before trade opening the issue is followed by a drift according or opposite to recommendations which causes the opening of a pairs trade. The trades yield small statistically not significant negative return. In trades where recommendations are issued after trade opening most of the negative return is made between trade opening and issue of recommendations. Only small and statistically not significant part of return is made between issue of recommendations and closing of trade in trades that are executed contrariwise to recommendations.

The only real effect that divergent recommendations have on the return is that when issued before trade opening, they are related to the breaking up of the pair which causes the spread to widen. The divergence of pairs triggers a pairs trade based on the originally estimated relationship. When the relationship does not hold anymore, the trade makes a loss. Effectively divergent recommendations are related to the divergence of pairs which causes negative returns. The aggregate abnormal positive return to pairs trading is completely driven by pairs that are not issued divergent recommendations.

Based on results the negative return to trades connected to divergent recommendations arises from two sources. Firstly from the unexplained breaking up of pairs before divergent recommendations are issued and secondly from the breaking up of pairs after issue of divergent recommendations. The first reason for break up is unexplained and analysts seem to react to the divergence in pairs. The second reason holds surprising information since pairs do not logically diverge in the direction of recommendations. Conclusion can be made that divergent recommendations are followed by divergence of the pair, but the recommendations do not hold any information about the direction.

Divergent recommendations are related to the divergence of the pair, whether issued before or after the divergence. Results indicate that an investor is better off not trading in the presence of divergent recommendations. Pairs that open after issue of divergent recommendations should be avoided and pairs that gain divergent recommendations after opening should be closed immediately. Investors can only escape part of the losses, since approximately half of the pairs connected to divergent recommendations are issued recommendations after the pair has diverged.

My results show that relative post-recommendation drift is not present in divergent recommendations. Results are contradictory with previous findings in Yu (2011). She finds that relative post-recommendation drift after the issue of divergent recommendations exists in pairs for 1, 3 and 6 months. She finds that the drift is large enough to be traded profitably. Yu (2011) trades divergence for up to six months whereas in my study I expect pairs to converge in short-term. According to trading divergence of the pair she finds that analyst recommendations are positively correlated with past stock price performance and thus accelerate the divergence. My results are also different in this sense since a small majority of divergent recommendations are issued in the direction to narrow the spread.

5.3.4. Difference in time preferences between statistical trading and analyst recommendations

A possible cause for not finding post-recommendation drift related to statistical pairs trading is the difference in time preferences. Statistical trading is a short-term strategy with a trading period of 6-months whereas analyst recommendations are often issued for a minimum time of 6 months, usually for one year. Average time a trade that is connected with divergent recommendations is open is 60 trading days matching to approximately 2.9 months. The time divergent recommendations are present is even lower, well below the recommendations' time span.

I test the difference in time spans by analyzing if the pairs that receive divergent recommendations are less often pairs in the following periods than pairs are on average. I include a group of pairs that receive only same recommendations from individual analysts in the tests. The group includes only pairs in which both stocks receive the same recommendations from the same analyst and do not receive divergent recommendations. Hypothesis is that these pairs would continue as pairs on a higher probability than pairs on average. Then pairs receiving divergent recommendations are actually diverging on the long-term instead of being converging on the short-term as statistical trading requires. The hypothesis is in line with findings in Lehmann (1990) who shows that short-term stock price changes are not indicative for longer term price changes that follow fundamental information. Therefore, analyst recommendations that reflect long-term fundamental information should not be connected to short-term price fluctuations reviewed in statistical pairs trading. This would explain my result that relative post-recommendation drift is not significant in statistical pairs up to a period of two months.

In my sample only 5.0% of all top 20 pairs are in the top 20 group also in the following formation period. Of pairs that receive divergent recommendations 4.4% continue as pairs and of pairs that receive same recommendations from individual analysts 7.5% continue as pairs.

The relations of the different groups indicate that the probability of continuing as a pair on the next period decreases if the pair receives divergent recommendations and increases if the pair receives same recommendations during trading. I further test the relation with a logit regression. Results show that the probability of being a pair in the next period decreases by 15-20% through divergent recommendations and increases by approximately 40% through same recommendations depending on regression specifications, but in most cases the coefficients are not statistically significant. The sample with only 5% of changeless pairs is too small to draw statistically significant conclusions.

The test structure is problematic since the persistence of pairs is studied with consecutive formation periods. As Figure 2 illustrates consecutive formation periods are actually overlapping by 6-months. Furthermore, the trading period during which divergent recommendations are issued overlaps with the final half of the second formation period. If recommendations are issued evenly during trading period, then the time recommendations can affect the pair during the second formation period is on average only a quarter of a year whereas pairs formation time before recommendation announcements on the second period is on average three quarters.

To deal with the issue, instead of studying the directly following formation period, I skip the period and analyze the period after that (original formation period +2). In Figure 2 the first formation period 1/2001 is matched with formation period 1/2002. Hence, the periods do not have any overlap. Moreover, the trading period 1/2001 overlaps with formation period 1/2002. The recommendations' issue date is thus included in the second formation period ensuring that rapid effects in stock prices after recommendation announcements are included in the analysis. The stock prices have also on average three quarters to show the post-recommendations drift and on average only one quarter of the second formation period takes place before recommendation announcements.

Even a smaller percentage of top 20 pairs remain on the formation+2 period than on the straight consecutive formation period with 5% of changeless pairs. Therefore, instead of regressing the probability of being a pair, as dependent variable I use a sum of squared deviations (SSD) ratio defined as the SSD of the pair on the formation+2 period divided by the average SSD of the top 20 pairs on that period. This affords me with a sample of 360 pairs with a non-binary dependent variable. Simple SSD is scaled to avoid the problem of high volatility periods with a large number of divergent recommendations dominating the regression. The final sample is 342 pairs, because 18 pairs are deleted from the data due to one or both stocks missing values on the formation+2 period.

Figure 5 shows the distribution of SSD ratios for three pair categories: pairs receiving divergent recommendations, pairs receiving only same recommendations and pairs in which both stocks do not receive recommendations from the same analyst (neutral). The distribution shows that the observations for same category are smaller than for divergent or neutral pairs. Unexpectedly observations for divergent pairs are somewhat smaller than for neutral pairs. The data includes one outlier observation of SSD ratio of 904 for one divergent recommendation pair. The observation is omitted from Figure 5 as well as from regression analysis.

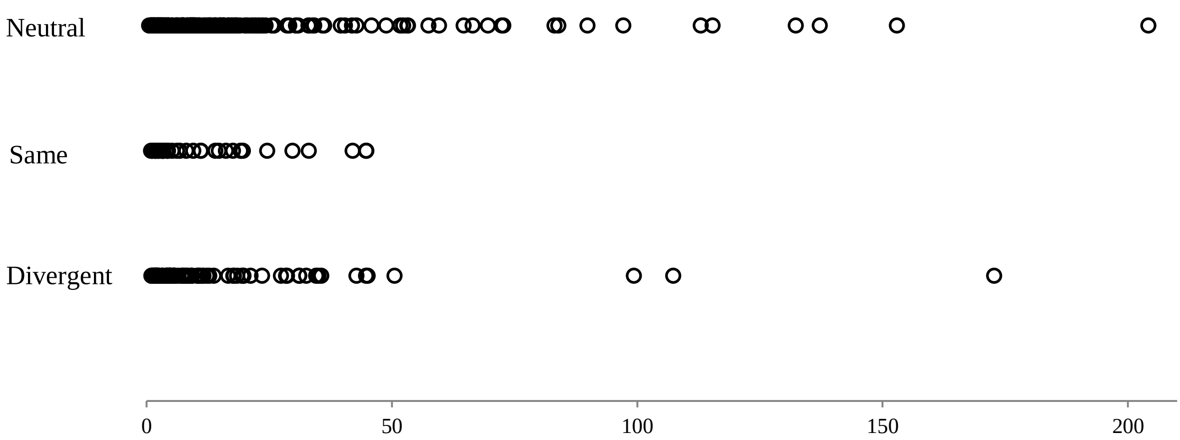
Regression results show that same recommendations have a negative impact on the formation+2 period SSD ratio. Surprisingly also impact from divergent recommendations is negative. Impact from same recommendations is stronger than from divergent recommendations. Most significant explanatory variable is SSD ratio during the original formation period. The higher the original ratio is, the higher the formation+2 period ratio. When original formation period SSD ratio is included in the regression, other variables are not significant with most specifications.

Pairs do not evidence consistent long-term post-recommendation drift after announcement of divergent recommendations. Hence, differences in time preferences do not explain the irrational post-recommendation drift observed in statistical pairs trades. Pairs that receive recommendations from a single analyst for both stocks, whether same or divergent, are closer than other pairs in the coming periods. Regression results are similar if absolute SSD, absolute change in SSD or percentage change in SSD is used as a dependent variable instead of the SSD ratio.

Figure 5

Distribution of sum of squared deviations ratio by recommendations to pair group

Figure 5 shows the distribution of sum of squared deviations (SSD) ratio by three pair groups: pairs that receive divergent recommendations during the original formation period (Divergent), pairs in which both stocks receive the same recommendations from the same analyst and do not receive divergent recommendations (Same) and pairs in which both stocks do not receive recommendations from the same analyst during the original formation period (Neutral). The period for which the SSD ratio is calculated is the original formation period +2. SSD ratio is calculated as the SSD of the pair divided by the average SSD of the top 20 pairs for the same period. One outlier observation of 904 for Divergent category is outside of the figure's range.



A plausible interpretation for the negative impact from divergent recommendations is that pairs, in which both stocks receive recommendations from the same analyst, are closer than neutral pairs that do not receive recommendations for both stocks from the same analyst. On average analysts follow a group of stocks. That group is formed on the basis of economics of scale of analyzing a single industry, close rivals or companies dependent on similar macro-economic factors for example. Despite the recommendations are divergent, if two stocks in a pair receive recommendations from the same analyst, they are close enough pairs for an analyst to follow them in tandem. If on the other hand a pair does not receive recommendations for both stocks from the same analyst, analysts do not consider them close enough substitutes to be analyzed jointly. Divergent recommendations do not indicate as strong relation as same recommendations, however, and might even indicate that a former close pair is on its way to divergence in the future.

6. Conclusions

In this thesis I examine the relation between statistical pairs and relative analyst recommendations with a U.S. stock and recommendation data over years 2000 to 2010. I conduct statistical pairs trading and match the trades with analyst recommendations. Specifically, I study whether statistical stock pairs are affected by the post-recommendations drift followed by divergent analyst recommendations between the stocks forming a pair.

Motivation for the study rises mainly from three sources. First, statistical pairs trading is popular among practitioners and it has been found to generate positive excess returns also in several scientific studies without any of them yet to find an explanation for the abnormal returns. Second, relative analyst recommendations have been shown to provide valuable information and pairs trading based on analyst recommendations has been shown to produce positive abnormal returns. And third, statistical pairs trading and analyst recommendations have not yet been combined in studies even though the two share a large amount of similar qualities and analyst recommendations have been found to be connected with stock prices as well as fundamental information.

In line with previous research I find statistical pairs trading to generate positive excess return. The return is smaller than in earlier papers, which is consistent with findings that excess return to the strategy is smaller in recent years. I also find support for both suggested reasons for the diminishing returns: increased pairs trading and hedge fund activity competing away the returns to arbitrageurs and an increasing number of pairs not converging back to equilibrium to enable profit, which signals an increasing fundamental risk in the trading strategy. Due to the smaller returns, the strategy does not survive an estimate of transaction costs unlike in previous papers.

Consistent with earlier studies I find significant evidence that analyst recommendations on average do provide valuable information to investors. I find analysts being able to issue correct level recommendations as well as identify relative winners in pairs of stocks. Relative recommendations seem to be more valuable to an investor as opposed to simple level recommendations, which is consistent with earlier findings and theory about bias in recommendations. Interestingly, I find relative recommendations between a statistically close stock pair being significantly more informative than relative recommendations within a whole industry.

Pairs, in which the stocks receive divergent recommendations issued by the same analyst, yield negative return to pairs trading. Divergent recommendations signal breaking up of the pair which causes negative returns. The pairs do not evidence expected relative post-recommendations drift in the direction recommendations indicate and hence the direction of recommendations does not give information on the future direction of the spread between a stock pair. Table 12 summarizes results on the studied hypotheses.

Table 12

Summary of hypotheses

H_1:	Statistical pairs trading generates positive abnormal returns.	Accepted
H_2:	Analysts' relative recommendations have investment value.	Accepted
H_{3a}:	Pairs trades opened after announcement of divergent recommendations yield abnormal negative returns.	Rejected
H_{3b}:	Pairs trades that receive divergent recommendations in the direction to widen the spread after the trade is opened yield abnormal negative returns.	Accepted
H_{3c}:	Pairs trades that receive divergent recommendations in the direction to narrow the spread after the trade is opened yield abnormal positive returns.	Rejected

H_{3a} and H_{3c} are rejected because the post-recommendations drift is not found significant. H_{3b} is accepted and pairs trades that receive divergent recommendations in the direction to widen the spread after the trade is opened are the main cause for the negative return to trades connected to divergent recommendations. The negative return is not due to significant post-recommendations drift, however, but due to significant unexplained negative return to the trade before the issue of divergent recommendations.

I study recommendations as information intermediaries to which stock markets react to. In parts of my results it is evident that analysts' recommendations reflect information that the stock markets have reacted to already before the recommendations are announced. Hence, the post-recommendations stock price drift is also small or nonexistent.

In aggregate, trades connected to divergent recommendations yield negative return due to high number of pairs breaking up. The abnormal positive return to statistical pairs trading is produced in its entirety by pairs that are not issued divergent recommendations. When pairs trading on convergence of the pair, an investor should not trade a spread that opens after announcement of divergent recommendations and correspondingly an open trade that is issued divergent recommendations should be closed immediately.

My results do not explain the irrational post-recommendations movement of the spread between stocks forming a pair. If analysts issue recommendations based on other public information, studies on the content of the original news could find reasons, why markets react differently to divergent recommendations in stock pairs than analysts expect.

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