# Sector Neutral Contrarian Strategies

- A study of short-term contrarian strategies in the Dow Jones STOXX 600

Christoffer Geijer Christofer Nordlander

ABSTRACT

This paper studies short-term contrarian strategies in the Dow Jones STOXX 600 between 1993 and 2008 taking on a sector neutral approach. The contribution to the literature is two folded. First, we investigate short-term contrarian strategies on an index covering 18 European countries. Second, we investigate the impact of the industry effect on short-term contrarian strategies. Short-term contrarian strategies are based on buying past loser and selling past winners. We investigate the profits derived from holding this strategy over one, two and three weeks following a week of formation. Practitioners in the hedge fund industry often restrict their long-short equity portfolios to be sector neutral, indicating that industry effects are of importance in risk management. We compare two zero-investment contrarian strategies where one has a reduced net exposure to industry effects (sector neutral strategy) and one is fully exposed to industry effects (generic strategy). Both strategies generate significant contrarian profits after controlling for risk, but when taking transaction costs in the form of bid-ask spreads into consideration profits disappear. Furthermore the sector neutral strategy proves superior to the generic strategy in terms of return to variability.

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## 1. Introduction

The purpose of this paper is to investigate whether short-term contrarian strategies are profitable in the European market and how an incorporation of the industry effect will affect contrarian strategies in the short-term.

The movement of stock prices puzzles practitioners and academics. While some rely on rational explanations others tend to find their answers in irrational behaviour of the human nature. One phenomenon that has occupied academics and developed into a field of its own is the tendency of stock prices to reverse. The prevailing theory in behavioural finance for these *price reversals* is, intuitively, that investors are bad decision makers and thus constantly *overreact* to information. The price reversal we experience is when stocks adjust to their intrinsic value. If this is a continuing process profitable strategies can be created, known in the literature as *contrarian strategies*, which buy past losing stocks and sell past winning stocks. However supporters of rational explanations constantly challenge this view. They argue that price reversals are explained by risk mismeasurement and other rational considerations such as transaction costs and measurement errors. When correctly accounting for these, the profits from contrarian strategies disappear. However using different methodologies across different markets, academics continue to yield abnormal profits, even after taking risk mismeasurement and other rational objections into consideration. From a rationalist's viewpoint this could imply that there are still sources of risk that are not correctly priced.

In parallel practitioners in the hedge fund industry, often restrict their long-short equity portfolios to be sector neutral, indicating that industry effects are of importance in risk management. Namely, controlling for the fact that firms in an industry reasonably are exposed to common industry specific risk factors to a larger extent than firms in other industries. Surprisingly, hardly any articles try to incorporate the industry effect into the context of contrarian strategies. Studies carried out (see Dreman and Lufkin 1997; Cohen and Polk 1998, Asness, Porter, and Stevens, 2000 and Bali, Demirtas, Hovakimian and Merrick, 2006), point in line with practitioners that the industry effect is a material factor when explaining risk, and have important implications on profits derived from these strategies. Grinblatt and Moskowitz (1999) study return persistence often referred to as momentum. They find in the medium term (6-12 months) that industry momentum almost entirely captures the return of single stock momentum. Stocks within industries tend to be much more highly correlated than stocks across industries. This indicates that momentum strategies are not very well diversified since winners and losers tend to be from the same industry. Grinblatt and Moskowitz suggests that there are hot and cold sectors in the economy and investors may simply herd towards or away from these sectors, causing price pressures that could create return persistence.

If industry momentum is present in the short-term, as we have experienced for financial stocks lately, this will be of importance for a contrarian strategist. Single stock contrarian strategies, which buy stocks from past losers and short stocks from past winners, are exposed to the risk of picking stocks in a past loser (winner) industry that consequently continue to lose (win) due to industry momentum. Thus it is motivated to investigate if industry exposure will have a material impact on portfolio formation in short-term contrarian strategies.

In this paper we investigate two different short-term contrarian strategies in the European market (Dow Jones STOXX 600). From an academics viewpoint it is of interest to further investigate the phenomena of contrarian strategies and the relation to an industry effect in the short-term. For the investor it is of interest whether profits are economically exploitable and if a correction for industry effects generates better performance in terms of return to variability. We argue that the thesis' contribution to the literature is two folded; first we investigate short-term contrarian strategies on a broad European index. Second, we investigate the impact of the industry effect on short-term contrarian strategies. To our knowledge the scope of this paper is motivated by a unique approach of investigating short-term contrarian strategies in the relation to the industry effect, presenting a straightforward trading strategy that takes industry-associated risk into consideration. The paper is organised as follows. In Section 2 we present the theoretical and empirical framework of previous research. In Section 3 we present our hypotheses, followed by Section 4 where we describe the data. Section 5 presents methodology and empirical findings while Section 6 concludes.

## 2 Theoretical and Empirical Framework of Previous Research

### *2.1 The Field of Short-term Contrarian Strategies*

In the literature there is rich evidence supporting negative serial correlation in stock prices (see Fama, 1965, Lo and MacKinlay, 1988 and 1990, Jegadeesh and Titman, 1993). The phenomenon of negative serial correlation is often referred to as price reversals. By constructing econometric models previous research has been able to forecast future prices based on historical ones, challenging the weak form of the efficient market hypothesis (EMH). In short, *contrarian strategies* refer to the construction of portfolios that are rebalanced at a predetermined time interval. Based on the previous period's return, one constructs a zero investment portfolio, taking a short position in the winners and a long position in the losers in an attempt of realising profitable returns based on price reversals. Alongside with the research on contrarian strategies another research field on inefficient markets has developed. By taking the opposite position, i.e. taking a short position in the losers while taking a long position in the winner, an investor believes in continuum in prices, referred to as a *momentum strategy*. In this chapter the most relevant research related to short-term (daily, weekly or monthly) contrarian profits will be presented. However to understand the context we first introduce a long-term (annual or longer) study initiating the field of research within behavioural finance on contrarian strategies.

In the context of long-term contrarian strategies De Bondt and Thaler (1985) formed, based on evidence from cognitive psychology, their overreaction hypothesis. It argues that investors are poor decision makers and overweight the importance of new information in relation to older information, this overreaction leads to excess optimism or pessimism, consequently driving prices upwards too far or downwards too far. Antoniou, Galariotis and Spyrou (2006) summarize:

> *The overreaction hypothesis asserts that extreme winners become losers in the ensuing period and vice versa, driven by an initial overreaction to news that is subsequently corrected. If this holds true, then contrarian strategies that are short in past winners and long in past losers should deliver profits* (Antoniou, Galariotis and Spyrou, 2006:840).

As a result, DeBondt and Thaler (1985), report long-term contrarian profits of up to 25% for their zero investment portfolio in the US market.

Even though there is a growing empirical support for short-term contrarian strategies, with the overreaction hypothesis as a primary explanation there is considerable evidence refuting this hypothesis as the primary source of profits. Key explanations undermining the overreaction hypothesis are (1) lead-lag effects, (2) risk mismeasurement, (3) firm-size effects, (4) trade volume, (5) infrequent trading and bid ask biases and (6) seasonality.

Lo and MacKinlay(1990) and Jegadeesh and Titman (1995) among others, confirm profitability for short-term contrarian strategies. However, Lo and MacKinlay decomposed weekly US stock prices to determine whether a lead-lag effect or an overreaction to firm-specific information explained most of the profits, their findings suggest that a lead-lag effect accounts for a majority of the contrarian profits. The return on large capitalization stocks almost always leads those of smaller stocks. They clarify their argument in a universe of two stocks.

> *Suppose the market consists of only the two stocks, A and B; if A's return is higher than the market today, a contrarian sells it and buys B. But if A and B are positively cross-autocorrelated, a higher return for A today implies a higher return for B tomorrow on average, thus the contrarian will have profited from his long position in B on average. Nowhere is it required that the stock market overreacts, that is, that individual returns are negatively autocorrelated* (Lo and MacKinlay, 1990:177).

In a response, Jegadeesh and Titman employed a modified decomposition methodology, with results challenging Lo and MacKinlay's conclusions. They found that less than 1% of the contrarian profits can be attributed to the lead-lag effect.

Others argue that the primary source for contrarian profits is risk mismeasurement. Fama and French (1996) invalidate the findings of De Bondt and Thaler (1985) pointing at multidimensional risk explanations. By adjusting for risk the significant patterns of price reversals disappears. However for short-term contrarian profits, Antoniou, Galariotis and Spyrou (2006) fail to refute the presence of overreaction as the driving source of profits (the discussion continues below).

Brown, Harlow and Tinic (1998) criticize the explanation that contrarian profits arise from systematic mispricing by investors. They argue that in the presence of imperfect information rational risk-averse investors often set stock prices before knowing the full ramifications of a favourable or unfavourable event. Then due to the uncertainties associated with the event investors set stock prices significantly below the conditional expected values. When the uncertainties associated with the event are resolved prices tend to move upwards on average, appearing as an underreaction to good news and an overreaction to bad news. For an individual event they find that it is next to impossible to predict the direction of the future returns since they appear to be random and that the following reaction is never significantly negative. Their findings contradict the overreaction hypothesis since there is no systematic mispricing and no reversal of winners.

Furthermore Chan (1988) challenge the notion of overreaction and market mispricing. By using the *Capital Asset Pricing Model*, accounting for time varying market risk, Chan finds that the negative serial correlations in returns are almost entirely attributed to variation in relative risks. This can be explained in the context of option pricing theory. Stocks whose values diminish become riskier because the change has greater effect on the market value of equity than on debt or debt like liabilities of the firms. The price fall of loser stocks increases the financial leverage of the loser firm and thus increases the risk of the stock. If we estimate the beta in the rank period without taking these changes in risk into consideration, the estimated beta will be a biased estimate of the beta in the test period, since the risk of the loser portfolio increases in the rank period. Losers' rank period beta underestimates the test period beta. While the opposite holds for the winners. Thus there is a variation in relative risks (see also; Ball and Kothari, 1989; Conrad and Kaul, 1989; Lo and MacKinlay, 1990).

Zarowin (1990) on the other hand, concludes that the size-effect is the source of De Bondt and Thaler's findings in line with Banz (1981) who finds that companies with small market capitalization outperform companies with large market capitalization, even after accounting for risk. Authors have provided rationale behind the size-effect. Chan and Chen (1991) argue that small and large firms have different sensitivities to risk factors important for pricing assets, and find in their sample of small firms a large proportion of marginal firms i.e. firms with low production efficiency and high financial leverage.

Conrad, Hameed and Niden (1994) test for the relation between lagged trade volume and short-term return patterns suggested by Blume, Easley, and O'Hara (1994) and Campbell, Grossman, and Wang (1993) and find that:

> *high-transaction securities experience price reversals, while the returns of low-transactions securities are positively autocovarying. Overall, information on trading activity appears to be an important predictor of the returns of individual securities* **(**Conrad, Hameed and Niden, 1994:1305).

While Blume, Easley, and O'Hara (1994) do not specify any particular rule; Campbell, Grossman, and Wang (1993) make specific predictions concerning the relation between trade volume and serial correlation of daily stock returns. They present a framework consisting of two types of market participants, *liquidity* (or *noninformational*) traders and *market makers* (risk-averse utility maximizers). The former group desire to sell stocks for exogenous reasons. The latter group is willing to accommodate this transaction, but they demand to be compensated in terms of a lower stock price and higher expected return. If the price of the stock changes due to exogenous shifts in demand, the expected return changes. An exogenous selling pressure imposed by liquidity traders causes the stock price to decrease more than its intrinsic value, compensating market makers for accommodating the sale. When liquidity traders are satisfied the stock price reverses back, hence showing the pattern of price reversals. Campbell, Grossman, and Wang (1993) give the rationale behind trading volume:

> *If a large subset of investors become more risk averse, and the rest of the economy does not change its attitudes towards risk, then the marginal investor is more risk averse, and in equilibrium, the expected return from holding the stock must rise to compensate the marginal investor for bearing the risk. Simultaneously, risk is reallocated from those people who become more risk averse to the rest of the market. The reallocation is observed as a rise in trading volume. Note that the rise in expected future returns is brought about by a fall in the current stock price that causes a negative current return. Therefore, a large trading volume will be associated with a relatively large negative autocorrelation of returns* (Campbell, Grossman, and Wang, 1993:924).

Bid-ask biases concern the movement of closing prices between bid and ask prices. As pointed out by Roll (1984), even in an informationally efficient market trading costs induce negative serial correlation. This has important implications for a contrarian strategist. When ranking stocks in portfolios based on past return, stocks with the highest positive (negative) returns are stocks likely to have their closing prices close to the bid (ask) price of yesterday and the ask (bid) price of today. When evaluating the next day's performance the closing price is no longer conditional and thus equally likely to end up being an ask price as being a bid price. This is known in the literature as the *bid-ask bounce*, and may induce an illusion of contrarian profits (see also Conrad and Kaul, 1993; Conrad, Kaul and Gultekin, 1997). Antoniou, Galariotis and Spyrou (2006) uses bid-to-bid prices to control for bid-ask bounce. They also find that bid prices exhibit lower volatility. They argue that lower volatility leads to lower extremes, which consequently leads to lower reversals. They persist to find short-term contrarian strategies after employing bid-to-bid prices. On top of that using closing prices ignores the *bid-ask spread* an investor faces when implementing contrarian strategies. At the beginning of the holding period the investor is buying (selling) the losers (winners) at the ask (bid) price. At the end of the holding period the positions are undone at the bid (ask) price. Thus Conrad and Kaul (1993), along with Conrad, Kaul and Gultekin (1997) argue that predictability is spurious due to these market frictions (or microstructure biases).

A well-documented phenomenon in the literature is the *January effect,* which implies that stocks, and especially small capitalisation (see Banz, 1981), earn above average risk-adjusted returns in January. This is primarily explained by two hypotheses, the tax-loss selling and window dressing hypothesis. The former refers to investors selling losers in December realizing losses for tax purposes and then reinvesting in January since the fundamental value is unchanged. The latter refers to cosmetically restructuring of portfolios, less known stocks with low past returns typically small capital stocks are sold in favour of well-known and successful large capital stocks. Later the portfolios are rebalanced to their original constituents (for a more elaborate discussion see D'Mello, Ferris and Hwang, 2003). It is questionable whether these hypotheses provide a satisfying answer to the January effect. An arbitrageur could easily buy these stocks in December and anticipate an abnormal value increase in January. Reinganum (1983) finds that small firms generate larger January returns independent on whether they showed capital gains or losses in the preceding period. Furthermore the January effect is found in markets without taxes on capital gains (see Van den Bergh and Wessels, 1985). More importantly, academics have found price reversals when controlling for the January effect (i.e. Zarowin, 1989; Antoniou, Galariotis and Spyrou, 2006).

According to growing research it is of importance to stress that short-term contrarian profits often are proved to be statistically significant even after controlling for the criticism presented above. Furthermore growing empirical evidence supporting profitable short-term contrarian strategies is found in other markets than the US (e.g. Chang, Mcleavey and Rhee, 1995 on Japan; Hameed and Ting, 2000 on Malaysia; Ni, Lui and Kang, 2002 on China; Bowman and Iverson, 1998 on New Zealand; Schiereck, DeBandt, and Weber, 1999 on Germany; Mun, Vasconcellos and Kish, 2000 on US versus Canada; Antoniou, Galariotis and Spyrou, 2001 on Greece; Antoniou, Galariotis and Spyrou, 2006 on UK). After controlling for risk, size, microstructure biases and seasonality they continue to find evidence of significant short-term contrarian profits.

However it follows naturally to ask if this is still the case after taking transaction costs into consideration. Conrad, Kaul and Gultekin (1997) among others, show that when controlling for transaction costs all short-term contrarian profits are extinguished. Lee, Chan, Faff and Kalev (2003) conclude that, when controlling for short selling and transaction costs, a contrarian strategy cannot be implemented as a stand-alone strategy but they argue that it may be value-enhancing when employed as an overlay strategy.

*2.2 Long-term Contrarian Profits and the Industry Effect*

On the topic of contrarian strategies, another field of research has been initiated. This one is motivated by the puzzling empirical results accredited to the excess performance of contrarian strategies favouring overweight in value (high book-to-market) and underweight in growth (low book-to-market) stocks. The main explanations are distress risk (Fama and French, 1992; 1993) and mispricing due to naïve investors expectations of future growth (Lakonishok, Shleifer, and Vishny, 1994). However  Bali, Demirtas, Hovakimian and Merrick (2006) point at another dimension of risk, namely industry specific risk.

Within an extensive literature, we only find four articles attempting to integrate industry effects into contrarian strategy analysis, namely Dreman and Lufkin (1997), Cohen and Polk (1998), Asness, Porter and Stevens (2000) and as noted above Bali, Demirtas, Hovakimian and Merrick (2006).

Dreman and Lufkin (1997) use data tapes from 1970-1995, examining intra-industry value rankings of firms sorted on earnings, book value and cash flow ratios. They find that industry neutral long-short portfolios could perform better than industry exposed market wide hedge portfolios in Sharpe ratio terms if industry effects on return risk are important. In addition, Cohen and Polk (1998) provide some evidence that industry-neutral long-short strategies improve Sharpe ratios under a sample period spanning from 1968 to1991. Asness, Porter and Stevens (2000) also compare market wide sorting on book value and cash flow ratios to intra-industry sorting based on the deviation of individual firm ratio from the industry mean. In their 1963-1998 sample, with their alternative sorting strategies they generate comparable returns and find that intra-industry returns have lower standard deviation. By investigating the speed and extent an individual firm's value ratios correct themselves towards the peer group median Bali, Demirtas, Hovakimian and Merrick (2006) construct equally-weighted semi-arbitrage portfolios.[1] By purchasing the cheapest stocks (i.e. high book-to-market) in each industry and selling the portfolio of richest stocks (i.e. low book-to-market) they compare their net returns to a generic contrarian strategy, constructed without regards to industry exposures based on relative value rankings across the full universe of firms. They find that; (1) narrow peer groups improve stock valuation; (2) mean reversion for deviations of an individual firm's ratios from its median is quite slow, i.e. more than one year; and (3) because of substantial differences in relative value average returns to contrarian portfolio strategies are statistically significant. Furthermore contrarian strategy portfolio

[1] First they form two portfolios, one with the cheapest and one with the richest, secondly they test the most extreme quintiles, and the net returns from both methodologies show consistent results.

performance is significantly improved in risk-adjusted terms when implemented in its industry-neutral hedging form vis-à-vis an industry exposed full-universe strategy, while both strategies produce close to identical average net returns of 6.8% per year. In all, previous research on long-term industry effect indicates that it contributes in explaining other dimensions of risk when implemented in contrarian strategies.

We conclude that in the *classical* field of contrarian strategies (referred to in section 2.1), academics construct portfolios on past returns across a full universe of stocks in the pursuit of long and short-term contrarian profits. While academics, focused on the industry effect (referred to in this section), construct portfolios based on financial ratios, primarily isolating the intra-industry effect in the long-term.

## 3. Hypotheses

In this section we draw upon previous research within contrarian strategies and research on the industry effect, where we intend to investigate an, to our knowledge, unexplored field namely the presence of short-term contrarian profits in the Dow Jones STOXX 600 and the presence of short-term contrarian profits incorporating the intra-industry effect. We ask ourselves if it is possible to find intra-industry short-term contrarian profits. If yes, is it possible through industry-neutral portfolio formation to create superior risk adjusted returns in comparison with a generic contrarian strategy? Thus the purpose of this paper is to investigate whether (1) contrarian profits exists in the Dow Jones STOXX 600 after taking risk, measurement errors and transaction costs into consideration and (2) whether this still is the case for a contrarian strategy with reduced exposure to industry effects. Moreover, from a practical standpoint (3) if a strategy, incorporating the industry effect, performs better than a conventional strategy on a return to variability basis.

We will construct two zero investment contrarian strategies where one has a reduced net exposure to industry effects and one fully exposed to industry effects; we name them the *sector neutral strategy* and the *generic strategy*. We expect that both the sector neutral and the generic strategy will yield significant contrarian profits. While the generic strategy will yield higher profits in comparison with the sector neutral strategy, the sector neutral strategy will, in terms of historical return to variability (i.e. Sharpe measure) perform better than the generic strategy due to its industry neutral construction. Next, we form our hypotheses:

Hypothesis 1: A *sector neutral strategy* and a *generic strategy* generate statistically significant positive raw returns.

Hypothesis 2: A *sector neutral strategy* and a *generic strategy* generate statistically significant positive risk-adjusted returns.

Hypothesis 3: A *sector neutral strategy* and a *generic strategy* generate statistically significant positive returns robust to measurement errors and transaction costs caused by bid-ask spreads.

Hypothesis 4: A *sector neutral strategy* is superior to a *generic strategy* in terms of historical return to variability, suggesting that industry effects have an impact on portfolio risk.

## 4. Data

This study uses weekly closing prices with reinvested dividends for all stocks in the Dow Jones STOXX 600, between January 1993 and December 2008. Constituents are gathered from STOXX Ltd (see reference list) and data points are collected from Datastream. Data is recorded in USD. Due to comparability we cannot apply local currencies. It is problematic to use the Euro primarily because of an ex ante currency conversion of data into Euro and secondly because there is not a uniform way to conduct this synthetic currency conversion. Thus by using USD, available for the whole data tape, a direct conversion from local currency to USD mitigates this problem. However the use of USD is not unproblematic as a currency exposure is introduced. The strategies simultaneously invest in 36 different stocks where no restrictions are made on currency. We argue that the currency exposure could potentially impose three major problems to the accuracy of our findings. Firstly, investigating past performance in different currencies always introduces the problem of differentiating on what is spurious currency effect and what is performance of the strategy. Secondly, if there is a rationally priced reversal effect on currencies this would distort the analysis. We find no arguments for such a process. Thirdly, the currency exposure introduces noise to the analysis which might invalidate the findings. This is a two-folded problem; the results may be falsely invalidated due to an increased variability with the currency exposure but the risk analysis might suffer from the currency exposure causing systematic risk to be attributed non-systematic risk. On the other hand using the Dow Jones STOXX 600 also has benefits. Firstly the Dow Jones STOXX 600 index is desirable because it has recorded liquid historical sector constituents; reducing problems associated with bid-ask biases and infrequent trading. Secondly, and most importantly, it allows us to use the historical sector classifications provided by STOXX Ltd and thus making the study of our sector neutral portfolios possible. In all the currency effect is undesirable but with our purpose to investigate the presence of contrarian profits in the European market controlling for industry effects the drawbacks are according to us unavoidable without taking on currency hedging strategies which is beyond the scope of this thesis.

The index is reviewed quarterly by STOXX Ltd and ranked by tradable market capitalisation, resulting in the possibility of a quarterly change in constituents. At every formation period the investor has a restricted investment universe. It consists of the stocks listed in the Dow Jones STOXX 600 at the beginning of each formation period. The constituents available on the index in Datastream are only the present constituents, not the historical set of constituents the investor was faced with at each time of portfolio formation. To overcome survivorship bias researchers often define a set of stocks in the beginning of the time series to represent the index. We have on the other hand used the actual stocks that were constituents on a given year according to the historical constituents list from STOXX Ltd.

Thus we mitigate the problem of survivorship bias by using the actual yearly constituents. Next, the Dow Jones STOXX 600 is categorized into sectors following the Industry Classification Benchmark (ICB) reviewed in Appendix 1. Thus far, the data consists of the yearly historical constituents of the Dow Jones STOXX 600 along side with the subordinated sector definitions. In addition to the fact that stocks must be a constituent on the Dow Jones STOXX 600 under the period of observation we impose the following conditions to the data; (1) prices must be quoted one year prior, (2) market capitalization and book values[2] must be quoted during the period under observation, (3) the constituents must have a unique identifier (i.e. ISIN or Sedol) in Dow Jones STOXX 600 for sector classification.

## 5. Methodology and Empirical Results

In the following section we define our trading strategies and the portfolio formation methodology used to derive contrarian profits from raw- and risk adjusted returns. Next we report on the methodology and the significance of the results from raw- and risk adjusted returns. This is followed by a test of the robustness to measurement error and transaction costs caused by bid-ask spreads. Finally we comment on the historical performance of the two trading strategies in terms of return to variability.

### *5.1 Portfolio construction*

We use investment strategies similar to Bali, Demirtas, Hovakimian and Merrick (2006). We will analyze the returns on two equally-weighted portfolios followed by value-weighted portfolios as a robustness check to potential size-effects. Within each sector, the stocks are ranked based on performance in the preceding formation week (F). Next, the one stock that has shown the weakest performance is placed in the loser portfolio and the one stock that has shown the strongest performance is placed in the winner portfolio. This is repeated for all 18 sectors creating a winner and loser portfolio with 18 stocks each.[3] These portfolios are held over holding periods corresponding to one, two and three weeks after formation (H1, H2 and H3 respectively). Next, we create a net return for each holding period by subtracting the equally-weighted average return of the winner portfolio from the equally-weighted average return of the loser portfolio. Economically speaking, this net return can be interpreted as the return on a zero investment portfolio, buying the losers and short-selling the winners in each industry, creating a net return series on a portfolio of pair-trades with reduced net exposure to industry effects (henceforth the sector neutral strategy). Next, we compare the performance of the strategy with a generic contrarian strategy. All stocks in the index are ranked based on performance in the preceding formation week (F), this time ignoring sector

[2] Negative book values are not eliminated (see Lakonishiok, Shleifer and Vishny, 1994, in contrary to Fama and French, 1993)

[3] For sector definition see Appendix 1.

classification. The portfolios are then created by placing the 18 stocks that have shown the weakest performance in the loser portfolio and the 18 stocks that have shown the strongest performance in the winner portfolio. The net return series is created by subtracting the equally-weighted average return of the portfolio of full-universe winner stocks from the equally-weighted average return of the portfolio of full-universe loser stocks (henceforth the generic strategy). This strategy may have exposure to any given industry.

As opposed to Ni, Lui and Kang (2002), we choose not to employ overlapping holding periods i.e. two or several portfolios of the same investment horizon held simultaneously. At any time the portfolio is rebalanced, the strategy closes out all positions taken in $t - H$. Using overlapping portfolios would induce autocorrelation in portfolio returns due to cross-dependence in portfolio formation, resulting in distorted t-statistics. More importantly, a problem with non-overlapping portfolios is that it reduces the number of observations affecting the ability to draw conclusions of the results. This would have been a severe problem with a smaller data set and longer holding periods. A schematic picture over the three different holding periods is presented below.[4]

**Figure 1: Portfolio construction**

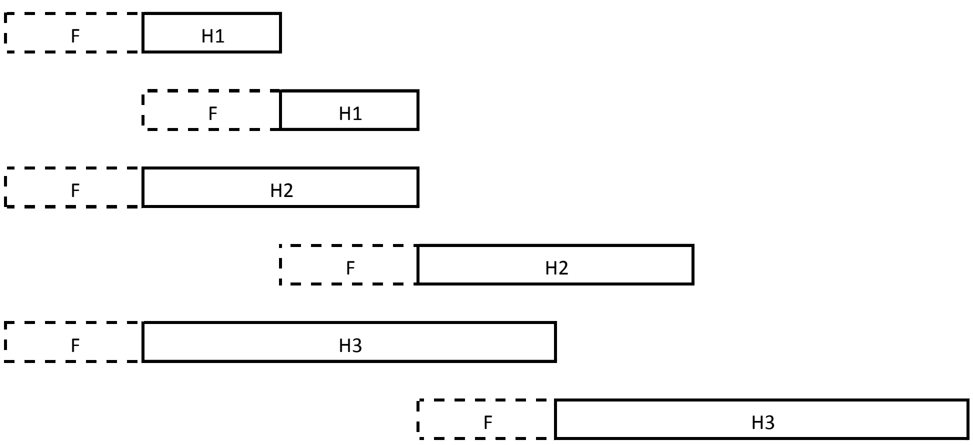


Figure 1 illustrate a schematic picture of portfolio construction over the three holding periods across the contrarian investment strategies. In the first week (formation week, F at $t_0$) all returns are ranked across a number of sectors ($n$). The best and the worst performing stocks in each sector are placed in a winner portfolio ($W_{sn}$) and a loser portfolio ($L_{sn}$) respectively, adding up to a total of $n$ stocks each. On parallel, the $n$ best and the $n$ worst performing stocks across the whole index are placed in a winner portfolio ($W_g$) and a loser portfolio ($L_g$). In total we have two winner portfolios and two loser portfolios all containing $n$ stocks each. The number of $n$ is equal to the number of represented sectors in the index. For Dow Jones STOXX 600 during the sample period $n$ corresponded to 17 sectors prior to year 2001 and 18 onwards (See Appendix 1:1). In the second week (at $t_1$) we take a short position in the winner portfolios ($W_{sn}$ and $W_g$) and a long position in the loser portfolios ($L_{sn}$ and $L_g$), holding them over one week, two weeks and tree weeks (H1, H2 and H3). The net positions (zero investment portfolios) for the different holding periods are $\pi_{sn}$ and $\pi_g$ given by ($L_{sn} - W_{sn}$) and ($L_g - W_g$) respectively. If the average return of the loser portfolio is higher than that of the winner portfolio reversal is declared.

[4] Note that the first week in January every year always starts with the first holding week since the constituents are reviewed.

The process described above will be conducted for (1) raw returns and (2) risk-adjusted returns. Before carrying out the strategies it is in place to follow up on the discussion initiated when forming our hypotheses, namely that we expect the generic strategy to yield higher returns than the sector neutral strategy, while the sector neutral strategy proves more efficient in terms of return to variability in relation to the generic strategy. We argue that this is primarily because the generic strategy at every formation window picks the full universe of extremes, while the sector neutral strategy picks intra-industry extremes thus limiting the up and downside related to momentum within industries.

Before moving on it is in place to elaborate on the construction of our sector neutral portfolio. Another methodology, involving pair-trades could be to condition the portfolio formation on extreme stocks, instead of sectors as we chose to do. Instead of selecting the extreme stocks in each sector, extreme stocks across the universe of stocks are paired with counterparts within each corresponding sector. This could generate larger profits since the extremes are chosen but this is achieved at the expense of diversification across sectors.

Either way both pair-trade strategies do dampen the exposure to industry effects. By taking opposite positions in two different stocks within the same sector, the net exposure to the sector is reduced. This being said, the sensitivity of the two stocks to the sector is not necessary symmetrical. In this sense our sector neutral portfolios dampen the exposure to industry-associated risk, but is in no sense strictly sector neutral due to this asymmetry. Let us exemplify with two companies, A and B, within the Oil and Gas Sector (0500). A's revenue stream is entirely dependent on oil, while B's revenue stream partially is dependent on renewable energy. Both companies react in the same manner to a change in oil prices, but due to the difference in revenue base, A is more sensitive to changes than B. If A was a past loser and B a past winner, we take a long position in A and a short position in B. As a result we would experience a net exposure to A's sensitivity to oil prices.

Summarizing, apart from oil prices there are various risk factors affecting various stocks in industries to a various extent. To sector neutralize one needs to look at the portfolio as an investment manager looks at a long/short market neutral portfolio.

Fundamental in investment management is an approach that eliminates equity market exposure, referred to as a market neutral strategy which is not simply achieved by holding two equally-weighted short and long portfolios. When conducting pair-trades, long and short positions are chosen independently of each other on the sole basis of extreme movement. To establish market neutrality Jacobs and Levy (1996) argue that neither the long nor the short position can be constructed separately. Selection of the securities to be held long should be determined simultaneously with the selection of securities to be sold short. This is because the flexibility to use offsetting positions on long and short sides is central to improve portfolio return and control risk, i.e. having perfectly symmetric and inversed betas. Thus only by regarding the portfolio as a single entity and neutralizing the exposure of the portfolio to the risk factor can true neutrality be reached regardless of whether this risk factor relates to the market or a sector (for more on portfolio optimization see Jacobs and Levy, 1998; Kwan, 1999).

As described, a more advanced way to achieve sector neutrality is to use a factor model neutralising the net exposure of the systematic risk to an underlying sector index. In Appendix 2 we regress the return series of pair-trades of stocks towards the sector index they belong to and find that (1) the systematic risk towards the sector indices are dampened (with an on average coefficient of 0.2337) and (2) that for some of the indices the pair-trades generate systematic risk exposure statistically indifferent from zero. Economically this suggests that if a sector moves by 1% in either direction, the sector neutral strategy on average moves in the same direction by 0.23%. This shows that the strategy is not strictly neutral but that it contributes to dampen the risk associated with the corresponding sector. Following the purpose of this paper, for a comparable analysis between strategies, we argue that potential benefits of sector neutralizing are satisfyingly captured in the simpler long-one short-one strategy employed.

### *5.2 Profitability of contrarian strategies based on raw returns*

Using the methodology described above the average returns for the different portfolios of the sector neutral and generic strategy is presented in Table 1 below.

**Table 1: Average raw returns during holding period H 1993-2008**

| **Sector Neutral Strategy** | *Average return* | *Std Err* | *Std Dev* | *t* |
|---|---|---|---|---|
| H1 | | | | |
| *Loser* | 0.733% | 0.120% | 3.453% | (6.13) |
| *Winner* | -0.351% | 0.094% | 2.726% | -(3.72) |
| *Loser-Winner* | 1.083% | 0.090% | 2.596% | (12.07) |
| H2 | | | | |
| *Loser* | 0.541% | 0.114% | 3.302% | (4.73) |
| *Winner* | -0.117% | 0.097% | 2.809% | -(1.20) |
| *Loser-Winner* | 0.658% | 0.087% | 2.514% | (7.57) |
| H3 | | | | |
| *Loser* | 0.419% | 0.112% | 3.246% | (3.73) |
| *Winner* | 0.042% | 0.101% | 2.921% | (0.42) |
| *Loser-Winner* | 0.377% | 0.081% | 2.353% | (4.62) |
| **Generic Strategy** | *Average return* | *Std Err* | *Std Dev* | *t* |
| H1 | | | | |
| *Loser* | 0.780% | 0.140% | 4.031% | (5.59) |
| *Winner* | -0.309% | 0.110% | 3.189% | -(2.80) |
| *Loser-Winner* | 1.089% | 0.114% | 3.295% | (9.55) |
| H2 | | | | |
| *Loser* | 0.574% | 0.132% | 3.811% | (4.35) |
| *Winner* | -0.146% | 0.114% | 3.300% | -(1.27) |
| *Loser-Winner* | 0.720% | 0.107% | 3.103% | (6.70) |
| H3 | | | | |
| *Loser* | 0.432% | 0.132% | 3.812% | (3.28) |
| *Winner* | -0.010% | 0.119% | 3.433% | -(0.09) |
| *Loser-Winner* | 0.442% | 0.111% | 3.195% | (4.00) |

The table reports the average raw return and descriptives for holdingperiod H during 1993-2008.

Table 1 reports equally-weighted average weekly returns of the loser (L), winner (W) and the difference of the loser and winner portfolios, i.e. the zero investment portfolio (L-W) over the various holding periods. In order to examine whether contrarian profits are attributable and to be able to compare the magnitude of these profits over the different holding periods' returns are presented as average weekly returns. Thus the return in H2 is the arithmetic average of the returns over the two following weeks of formation. The difference between the loser- and the winner portfolios is the difference of these average weekly returns in line with Ni, Lui and Kang (2002). Thus if the difference between the loser portfolio and the winner portfolio (L-W) is statistically significantly larger than zero then contrarian profits exists. However whether these are economically meaningful remains to be investigated. Here it is in place to comment on the distribution of the returns. We do not have an issue with the assumption on the underlying distribution since with the large data set, the requirement of the central limit theorem is fulfilled. Table 1 reports statistically significant short-term contrarian profits for all 6 zero investment portfolios at any reasonable significance level. This follows logically, when studying the winner and loser portfolios separately it is evident that both portfolios, across strategies, show strong patterns of reversion. At a first glance the profits that arise from both contrarian strategies are staggering yielding an annualised average return of approximately 56% for both strategies. Putting it into context the Dow Jones STOXX 600 yielded an average annualised return of 7% with a comparable variability (the standard deviation of the market portfolio is even slightly higher than the sector neutral strategy for the same number of observations in the sample period, annualised 18.7% versus 18.5%). Looking at the different H investment horizons the contrarian profits decrease over the holding periods. Judging from the t-statistics reported for the zero investment portfolios across strategies, the test statistics suggest that most of the contrarian profits are captured in the first holding week (H1), and then diminishing over the following weeks (H2, H3). To confirm this, we isolated the contrarian effects in each period, i.e. each holding week H now corresponds to the return captured in that particular week following the formation week. For example H2 is no longer the arithmetic average of the two following weeks of formation, but the return captured in the second week after formation. The procedure shows that for both the generic and the sector neutral strategies we see contrarian profits, primarily captured in the first week (H1) after formation and then diminishing over the following weeks (H2, H3), see Table 2 on the next page. [5]

[5] The average return in each holding period (H) is based on the portfolio formation (F), lagged H weeks in an overlapping sequence, increasing the number of observations and increasing the robustness following thereof.

**Table 2: Raw returns for holding week H 1993-2008**

| Sector Neutral Strategy | Holding week (H) | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| L | 0.733% | 0.373% | 0.147% |
| | (6.13) | (3.25) | (1.26) |
| W | -0.351% | 0.133% | 0.135% |
| | -(3.72) | (1.42) | (1.34) |
| L-W | 1.083% | 0.240% | 0.012% |
| | (12.07) | (2.94) | (0.15) |
| Generic Strategy | | | |
| L | 0.780% | 0.330% | 0.099% |
| | (5.59) | (2.40) | (0.74) |
| W | -0.309% | 0.052% | 0.189% |
| | -(2.80) | (0.47) | (1.69) |
| L-W | 1.089% | 0.278% | -0.090% |
| | (9.55) | (2.49) | -(0.85) |

The table reports the average weekly return for each holding week during the period 1993-2008. Each holding week H; now correspond to the return captured in that particular week following the formation week. For example H2 is no longer the arithmetic average of the two following weeks of formation, but the average return captured in the second week after formation. The t-statistics are shown in parentheses.

Both strategies report statistically significant weekly contrarian profits in H1 and H2. The generic strategy reports 1.089% and 0.278% in H1 and H2 respectively while the corresponding figures for the sector neutral strategy is 1.083% and 0.240% for each holding week. In H3 neither strategy yields statistically significant contrarian profits. Interestingly the generic strategy generates negative returns on average. To further validate our findings we investigated the autocorrelation of the full sample. The data confirms negative autocorrelation in the first week following formation (-0.0343), and positive autocorrelation in the two weeks after (0.0059 and 0.0048 respectively). Back to the average weekly returns over the holding periods (Table 1), the t-statistics are higher over the holding periods for the sector neutral strategy in comparison with the generic strategy, given that the standard errors of the sector neutral strategy are lower than the standard errors of the generic strategy. As we argued above, most of the contrarian profits are captured in the first week following formation. Thus this week is of central interest in our analysis of contrarian profits. Noteworthy at this stage is that in H1, both strategies yield about the same profits (the generic yielding slightly higher) however looking at the t-statistics there is less variation of the return of the sector neutral strategy in relation to the generic strategy. This pattern is persistent over all holding periods. This is in line with what we expected since the generic strategy at every formation window picks the full universe of extremes, while the sector neutral strategy picks intra-industry extremes thus limiting the up and downside. At this stage these findings suggest that the industry effect indeed has an impact on portfolio formation. However before drawing any conclusions this needs to be investigated further. Both H1 strategies show high activity where 93% of the invested capital is reallocated weekly to new stocks at each time of formation. This is indeed an extremely actively managed portfolio, which presumably is associated with high transaction costs. One criticism toward the robustness of our findings is that unlike Ni, Lui and Kang (2002), we consider fewer and shorter periods for portfolio formation and holding. On the other hand we use two separate strategies with different selection algorithms. This far we conclude that contrarian profits are of material magnitude and statistically significant on the Dow Jones STOXX 600, and primarily captured in the first week following formation. We record annualised average return of 56% suggesting exploitable investment opportunities; however this is before taking plausible transaction costs and market rigidities such as short selling constraints into consideration. At this stage we confirm our first hypothesis, namely that both the generic- and the sector neutral strategy yield statistically significant raw returns. Next it follows naturally to ask, whether these findings are robust to various measures of risk, or expressed differently, if an investor can yield abnormal contrarian profits not attributable to additional risk taking.

### *5.3 Profitability of contrarian strategies based on risk-adjusted returns*

Referring to previous research, if risk explains part of the findings it is more appropriate to use risk-adjusted returns to test for contrarian profits. The methodology for risk-adjusted returns is similar to the one of raw returns. First, however, the risk-adjusted returns need to be estimated. This is done using two embedded models, (1) the *Capital Asset Pricing Model* (henceforth CAPM) and (2) the Fama and French (1993) three-factor model (henceforth 3FM). This is motivated by the fundamental impact the aforementioned models have had on asset-pricing literature. Above all the 3FM is motivated due to its ability to explain long-term price reversals in the US. The CAPM links an excess asset return to the risk premium of the market portfolio, while the 3FM in addition takes into account the size and value effect. The stochastic regression of CAPM is defined below (see Ni, Lui and Kang, 2002):

$$\left(r_{pt} - r_{ft}\right) = \alpha_p + \beta_p\left(r_{mt} - r_{ft}\right) + \varepsilon_t \quad P\begin{cases} W \\ L \end{cases} \tag{1}$$

$$\left(r_{Lt} - r_{Wt}\right) = \alpha_c + \beta_c\left(r_{mt} - r_{ft}\right) + \varepsilon_t \tag{2}$$

where $\left(r_{pt} - r_{ft}\right)$ is the H week excess return of portfolio $p$, or more precise the difference between the nominal H week return of portfolio $p$ and the risk free rate of the corresponding period. Furthermore $r_{Lt}$ and $r_{Wt}$ are the losers' and winners' raw returns. $\left(r_{mt} - r_{ft}\right)$ is the difference between the nominal H week return of the stock market index (Dow Jones STOXX 600) and the risk free rate of the same period, or the market risk factor. $\alpha$ is the pricing error of the equation and $\beta$ is the slope coefficient, the subscripts $p$ and $c$ refer to portfolio or contrarian strategy coefficients. $\varepsilon_t$ is the error term robust to autocorrelation and heteroscedasticity by conducting a regression with Newey-West standard errors.

As mentioned Fama and French (1993, 1996) argue that expected returns are better depicted by three factors, (1) the excess return of a broad market portfolio; (2) the difference between the return of a portfolio of small stock and the return of a portfolio of large stocks (SMB) and (3) the difference between the return of a portfolio of high book-to-market (value) stock and the return of a portfolio of low book-to-market(growth) stocks (HML). The stochastic regression of the 3FM is defined below:

$$(r_{pt} - r_{ft}) = \alpha_p + \beta_p(r_{mt} - r_{ft}) + \gamma_p(SMB_t) + \varphi_p(HML_t) + \varepsilon_t \quad P\begin{cases} W \\ L \end{cases} \tag{3}$$

$$(r_{Lt} - r_{Wt}) = \alpha_c + \beta_c(r_{mt} - r_{ft}) + \gamma_c(SMB_t) + \varphi_c(HML_t) + \varepsilon_t \tag{4}$$

where the excess return of portfolio $p$, the losers' and winners' returns $r_{Lt}$ and $r_{Wt}$ and the market risk factor are defined as above. Where $\alpha$, $\beta$, $\gamma$ and $\varphi$ are the coefficients with the corresponding subscripts as above. To construct the factors for the Dow Jones STOXX 600 market values and book-to-market values for the constituents are obtained from Datastream. The SMB and HML are constructed from six value-weighted portfolios (S/L, S/M, S/H, B/L, B/M, B/H) in line with Fama and French (1993). The SMB is calculated as the difference between the simple average of the returns of the three small stock portfolios (S/L, S/M and S/H) and the three big stock portfolios (B/L, B/M and B/H).[6] The HML is calculated as the difference between the simple average of returns of the high book-to-market (S/H and B/H) portfolios and the low book-to-market portfolios (S/L and B/L). The average weekly risk premium for the market minus the risk free rate, SMB and HML are reported in Table 3 below.

**Table 3: Asset pricing factors**

| Year | Rm-rf | SMB | HML |
|---|---|---|---|
| *1993* | 0.366% | 0.150% | 0.353% |
| *1994* | -0.073% | 0.059% | 0.121% |
| *1995* | 0.220% | -0.063% | -0.111% |
| *1996* | 0.216% | 0.059% | -0.147% |
| *1997* | 0.279% | -0.219% | 0.432% |
| *1998* | 0.419% | -0.396% | 0.060% |
| *1999* | 0.221% | -0.019% | 0.063% |
| *2000* | -0.311% | -0.076% | 0.361% |
| *2001* | -0.485% | 0.046% | 0.459% |
| *2002* | -0.452% | 0.011% | 0.542% |
| *2003* | 0.587% | 0.148% | 0.304% |
| *2004* | 0.356% | 0.116% | 0.143% |
| *2005* | 0.078% | 0.031% | 0.239% |
| *2006* | 0.463% | 0.140% | 0.246% |
| *2007* | 0.145% | -0.247% | -0.217% |
| *2008* | -1.165% | -0.174% | -0.305% |
| **Total** | **0.055%** | **-0.027%** | **0.159%** |

Table 3 reports the average weekly risk premium of the market minus risk free rate, Small Minus Big and High Minus Low.

[6] Ranked on size and grouped into two portfolios, *Small* and *Big* (S and B) and ranked on book-to-market into three portfolios, grouping the bottom 30% as *Low* (L), the middle 40% as *Medium* (M) and the top 30% as *High* (H).

Embedded in both asset-pricing models is the risk free return. Vaihekoski (2007) argues that in an international setting the risk free return has to be measured in the same numeraire currency as the asset returns are measured (USD), using the shortest available rate of return closest to the time period under estimation (weekly). The return is, due to data availability, calculated using prices from the secondary market of the 3-month US Treasury bill total return index provided by Datastream (for a further discussion see Vaihekoski, 2007).

Commenting on the factors presented in Table 3, the market premium is considerably lower than the contrarian profits obtained in section 5.2. The SMB is on average negative due to influential negative movements of small stocks in the index during the sample period. The HML on the other hand is positive implying that value stocks have earned on average higher returns than growth stocks. The corresponding results from Fama and French's factors (see reference list) on the NYSE, AMEX, and NASDAQ indicate a small but positive premium for SMB and a larger positive HML factor. The difference between our SMB factors and the one recorded by Fama and French might be explained by the different base for their index containing a broader spectrum of stocks in terms of size.

Next, we estimate the risk-adjusted (or abnormal) return ($\alpha$) by regressing the CAPM and the 3FM (eq. 1 to 4). When estimating coefficients with least squares, standard errors are designed to allow for heteroscedasticity and autocorrelation, (see Gujarati, 2003) based on Newey-West adjustments to the error term.[7] Thus each H week portfolio (18 in total) is regressed against (1) the CAPM and (2) 3FM producing 36 regressions, estimating the abnormal return for each H week portfolio. The average risk-adjusted returns for the different strategies and portfolios are presented on the next page in Table 4 when accounting for the market risk (eq. 1 and 2).

In Table 4 we observe the average abnormal returns of the two investment strategies across the holding periods, accompanied with the factor loadings for the CAPM. We find in line with Wang (2004) that all beta values for both strategies' winner and loser portfolios are highly statistically significant, suggesting that common return factors are fundamentally related to the way in which investors set prices. We also find that most alphas are statistically significant, suggesting that there are dimensions of return not being explained by systematic risk. After taking risk into consideration, the annualised abnormal returns are of the same magnitude as the raw returns, approximately 53% per annum. For an investor employing a contrarian strategy this indicates that a major part of the returns can be earned free from the systematic risk of the market. Given the small factors reported in Table 3 these findings are not surprising since it would require the strategies to have extremely high exposure to the factors.

[7] Regressing with H lags in the corresponding H period regression, i.e. a portfolio with H3 weeks is allowing for a lag of 3.

**Table 4: Capital Asset Pricing Model**

| **Sector Neutral Strategy** | α | *t* | β | *t* |
|---|---|---|---|---|
| H1 | | | | |
| *Loser* | 0.600% | (8.69) | 1.10458 | (23.15) |
| *Winner* | -0.469% | -(7.81) | 0.84172 | (22.26) |
| *Loser-Winner* | 1.069% | (11.98) | 0.26286 | (3.72) |
| H2 | | | | |
| *Loser* | 0.411% | (6.00) | 1.04454 | (22.70) |
| *Winner* | -0.237% | -(4.10) | 0.88016 | (28.16) |
| *Loser-Winner* | 0.648% | (7.38) | 0.16438 | (2.53) |
| H3 | | | | |
| *Loser* | 0.290% | (4.23) | 1.03541 | (27.21) |
| *Winner* | -0.081% | -(1.41) | 0.92775 | (24.03) |
| *Loser-Winner* | 0.371% | (4.44) | 0.10766 | (2.23) |
| **Generic Strategy** | α | t | β | t |
| H1 | | | | |
| *Loser* | 0.714% | (7.58) | 1.21180 | (16.56) |
| *Winner* | -0.361% | -(4.89) | 0.93878 | (19.93) |
| *Loser-Winner* | 1.075% | (9.15) | 0.27302 | (2.58) |
| H2 | | | | |
| *Loser* | 0.512% | (5.56) | 1.12029 | (18.30) |
| *Winner* | -0.201% | -(2.88) | 1.00079 | (24.95) |
| *Loser-Winner* | 0.714% | (6.27) | 0.11950 | (1.45) |
| H3 | | | | |
| *Loser* | 0.371% | (4.18) | 1.11061 | (23.50) |
| *Winner* | -0.068% | -(0.90) | 1.04441 | (25.46) |
| *Loser-Winner* | 0.439% | (3.93) | 0.06620 | (1.16) |

The table shows factor loading (β) and intercept (α) for the Capital Asset Pricing Model during 1993-2008 using the Newey-West procedure of standard errors, generating t-statistics robust to autocorrelation and heteroscedasticity.

Now recapitulate on the selection algorithm of the sector neutral portfolio, in each formation period the sector neutral strategy selects stocks in sectors, placing the extremes in loser and winner portfolios, while the generic strategy selects full-universe extremes. At this stage we conclude that the generic strategy on average picks stocks with higher beta than the sector neutral strategy. Like Chan (1988) our results show that on average losers tend to be more risky than winners, i.e. loser portfolios generate higher beta values than winners across strategies and holding periods. The asymmetry is slightly larger for the generic strategy in H1 vis-à-vis the sector neutral portfolio. More interesting when looking at the zero investment portfolios for the holding periods H2 and H3 we find that the sector neutral strategy generates a higher net beta exposure than what is the case for the generic strategy, suggesting that the selection algorithm of the sector neutral portfolio poses constraints to beta neutralization. In all, the sector neutral strategy generates significant betas across all holding periods, while the generic strategy only produces a significant beta for the first holding period, suggesting that market risk cannot explain the abnormal returns in H2 and H3 for the generic strategy due to better symmetry of beta exposure. With this being said, the generic strategy on average generates slightly higher abnormal returns over the holding periods vis-à-vis the sector neutral strategy. On the other hand, the variability in abnormal returns is consequently lower for the sector neutral strategy's loser, winner and zero investment portfolio over all holding periods. Recapitulate on what we discovered in the previous section, namely that most of the contrarian profits appear in the first week following formation. H2 and H3 could rather be treated as control points, assuring that the full effect is captured. In H1, the generic strategy shows a slightly larger beta exposure than the sector neutral strategy.

In all, we see a distinct pattern. (1) The generic strategy's winner and loser portfolios generate slightly higher betas than the sector neutral strategy. (2) Losers are riskier than winners. (3) This asymmetry generates a significant beta exposure for the zero investment portfolio in H1. (4) The asymmetry is slightly larger for the generic strategy in H1 vis-à-vis the sector neutral portfolio, whilst in H2 and H3 the opposite holds.

To conclude, in H1 both strategies generate more or less the same average abnormal returns at the same level of beta exposure to the loser portfolios. For an equal amount of stocks in both strategies the sector neutral strategy generates lower variability in abnormal returns, thanks to, we argue, its sector neutral approach. This in turn, because the generic strategy's selection algorithm can allocate all long- or short positions to a specific sector and thus co-vary to a larger extent than the sector neutral strategy. The sector neutral strategy is forced to diversify across industries making it less sensitive to industry risk and momentum.

**Table 5: Fama French Three Factor Model**

| **Sector Neutral Strategy** | *a* | *t* | β | *t* | γ | *t* | φ | *t* |
|---|---|---|---|---|---|---|---|---|
| H1 | | | | | | | | |
| *Loser* | 0.604% | (9.53) | 1.19366 | (25.80) | 0.58836 | (7.19) | 0.04678 | (0.64) |
| *Winner* | -0.455% | -(8.58) | 0.94257 | (25.39) | 0.67183 | (9.83) | -0.00810 | -(0.15) |
| *Loser-Winner* | 1.059% | (12.00) | 0.25109 | (3.55) | -0.08347 | -(0.82) | 0.05488 | (0.61) |
| H2 | | | | | | | | |
| *Loser* | 0.419% | (6.45) | 1.13685 | (25.27) | 0.61155 | (6.95) | 0.02522 | (0.30) |
| *Winner* | -0.233% | -(4.43) | 0.97561 | (32.49) | 0.63005 | (9.54) | 0.05018 | (0.85) |
| *Loser-Winner* | 0.652% | (7.33) | 0.16123 | (2.61) | -0.01850 | -(0.17) | -0.02496 | -(0.24) |
| H3 | | | | | | | | |
| *Loser* | 0.289% | (4.73) | 1.13408 | (35.96) | 0.64851 | (5.78) | 0.08527 | (1.29) |
| *Winner* | -0.066% | -(1.21) | 1.02923 | (25.94) | 0.67639 | (9.91) | -0.00816 | -(0.12) |
| *Loser-Winner* | 0.355% | (4.18) | 0.10486 | (2.13) | -0.02788 | -(0.21) | 0.09344 | (1.16) |
| **Generic Strategy** | α | *t* | β | *t* | γ | *t* | φ | *t* |
| H1 | | | | | | | | |
| *Loser* | 0.765% | (8.66) | 1.32969 | (18.89) | 0.80548 | (8.12) | -0.22358 | -(2.33) |
| *Winner* | -0.321% | -(4.48) | 1.05229 | (22.03) | 0.77009 | (9.76) | -0.15665 | -(1.84) |
| *Loser-Winner* | 1.086% | (9.17) | 0.27739 | (2.64) | 0.03539 | (0.30) | -0.06693 | -(0.55) |
| H2 | | | | | | | | |
| *Loser* | 0.569% | (6.28) | 1.24025 | (21.23) | 0.82251 | (7.37) | -0.25220 | -(2.18) |
| *Winner* | -0.173% | -(2.54) | 1.11151 | (28.46) | 0.74454 | (9.29) | -0.08245 | -(0.96) |
| *Loser-Winner* | 0.743% | (6.22) | 0.12874 | (1.65) | 0.07797 | (0.62) | -0.16976 | -(1.27) |
| H3 | | | | | | | | |
| *Loser* | 0.414% | (5.02) | 1.24051 | (30.00) | 0.88048 | (6.60) | -0.15960 | -(1.38) |
| *Winner* | -0.017% | -(0.21) | 1.15836 | (26.04) | 0.78015 | (9.25) | -0.21903 | -(1.97) |
| *Loser-Winner* | 0.431% | (3.70) | 0.08215 | (1.40) | 0.10032 | (0.67) | 0.05942 | (0.37) |

Table 5 illustrates intercept and factor loadings of the three factor model during 1993-2008 using the Newey-West procedure of standard errors, generating t-statistics robust to autocorrelation and heteroscedasticity. β is the market slope coefficient, γ the SMB slope coefficient and φ the HML slope coefficient.

Next, we compliment our findings from the CAPM regressions with the findings of the 3FM (eq. 3 and 4). In Table 5 we observe the average abnormal returns for both investment strategies across the holding periods, accompanied with the factor loadings for the 3FM. After taking the risk factors embedded in the 3FM into consideration, the abnormal returns for all holding periods across strategies remain statistically significant for the zero investment portfolios. More importantly, this shows that the contrarian profits are not explained by the risk modelled for. Commenting on the slope coefficients for the winner- and loser- portfolios separately, we find that the betas are once again highly statistically significant for all portfolios over the holding periods. The same holds for the SMB slope coefficient implying that the risk associated with firm size contributes to explaining the returns of the winner and loser portfolios. The HML slope coefficient on the other hand only proves statistically significant in some periods, and that is for the generic strategy only (H1 and H2 for the loser portfolio, and H3 for the winner portfolio). None of the SMB- and HML slope coefficients are statistically significant for the zero investment portfolios across strategies and holding periods suggesting that the risk exposure to firm size and value is negligible. This being said, even though not statistically significant it is interesting to note that the net exposure to the size factor differs across strategies. The sector neutral strategy is inversely related to the SMB factor while the opposite holds for the generic strategy over the holding periods. This can be interpreted as the winners behave more like small stocks than the losers do in the sector neutral portfolio, while the losers behaving more like small stocks than the winners do in the generic strategy. Furthermore in absolute terms, the sector neutral strategy’s winners generate larger alphas than the generic strategy’s winners over the holding periods, while the opposite holds for the losers. Overall the generic strategy has higher factor loadings towards the SMB than the sector neutral strategy. It appears that the generic strategy, at each time of formation, is more likely to on average place stocks sensitive to the SMB factor in its portfolios, generating a net exposure that on average is exposed to smaller stocks in contrast to the sector neutral strategy. The sector neutral strategy is restricted to choosing stocks across industries, where the critical size for firms to operate reasonably can vary. Next, to confirm our suspicion we investigate the mean and median properties for the winner and loser portfolios across strategies. Our findings are presented in Table 6 below.

**Table 6: Average and Median Market Values and Book-to-market values**

| | Market Value | | Book-to-Market Value | |
|---|---|---|---|---|
| Industry Strategy | | | | |
| L | 7 832.92 | (3430) | 0.575 | (0.488) |
| W | 7 565.49 | (3393) | 0.611 | (0.503) |
| Generic Strategy | | | | |
| L | 7 448.22 | (3014) | 0.584 | (0.476) |
| W | 7 324.51 | (2963) | 0.614 | (0.498) |
| Total | 10 157.14 | (3960) | 0.582244 | (0.493) |

Table 6 illustrates the average (median) market and book-to-market values for the winner and loser portfolios across strategies

Table 6 confirms that (1) the loser portfolios on average contain firms with lower book-to-market ratios than the winner portfolios across strategies (2) the generic strategy on average picks smaller stocks than the sector neutral strategy and (3) that the winner portfolios on average contain smaller stocks than the loser portfolios. If (1), (2) and (3) hold then the generic portfolio chose riskier losers than the sector neutral portfolio. This is in turn because the loser stocks of the generic portfolio exhibit larger sensitivity to the SMB factor than the winners even though the losers are larger on average.

Losers are on average larger than winners. Thus winners should have a larger exposure to the SMB factor than losers. Consequently, the zero investment strategy should have a negative exposure to the SMB factor. What has been stated is true for the sector neutral strategy but not true for the generic strategy. This could be a result of using equally-weighted portfolios. To further investigate whether this is the case a value-weighted approach is conducted to control for a possible overstatement of the relative importance of smaller stocks, i.e. a size effect. The value-weighted return of each portfolio is computed as $r_p^v = \sum r_i w_i$ where $r_i$ is the H holding period return of the *i*th stock and $w_i$ is the market value in the beginning of the year to the total market value of the portfolio. A remarkable note for the reader is that the overall result using a value-weighted methodology as opposed to an equally-weighted on raw returns for the zero investment portfolios did not alter the economic significance of the strategies.[8] The use of yearly data on market value limits the scope of the analysis but we argue it serves the purpose of investigating the size effect. The results from the 3FM using value-weighted portfolios are presented in Table 7. In H1 the net exposure of the zero investment portfolios towards the market factor increases. Simultaneously the SMB factor decreases in magnitude for both strategies, now generating an expected inverse net exposure to the SMB for both strategies. Reasonably because when taking size into consideration the large low-beta winners are given larger weighting.

[8] The sector neutral strategy showed a decreased return on average (1.068% versus 1.083%) whilst the generic strategy increased (1.152% versus 1.089%).

**Table 7: Fama French Three Factor Model using Value-Weighted Portfolios**

| Sector Neutral Strategy | α | *t* | β | *t* | γ | *t* | φ | *t* |
|---|---|---|---|---|---|---|---|---|
| H1 | | | | | | | | |
| *Loser* | 0.592% | (6.90) | 1.19203 | (12.53) | 0.00275 | (0.03) | -0.00370 | -(0.03) |
| *Winner* | -0.392% | -(5.89) | 0.84703 | (16.56) | 0.20360 | (2.68) | -0.05523 | -(0.70) |
| *Loser-Winner* | 0.984% | (8.51) | 0.34500 | (3.08) | -0.20086 | -(1.69) | 0.05153 | (0.38) |
| H2 | | | | | | | | |
| *Loser* | 0.406% | (5.85) | 1.08051 | (18.52) | 0.15993 | (1.75) | -0.08023 | -(0.92) |
| *Winner* | -0.179% | -(2.94) | 0.91364 | (21.76) | 0.09244 | (1.17) | 0.00713 | (0.10) |
| *Loser-Winner* | 0.585% | (6.07) | 0.16687 | (2.55) | 0.06749 | (0.53) | -0.08736 | -(0.79) |
| H3 | | | | | | | | |
| *Loser* | 0.243% | (3.47) | 1.09527 | (25.69) | 0.19924 | (1.63) | -0.00374 | -(0.05) |
| *Winner* | -0.111% | -(1.51) | 1.01392 | (16.52) | 0.13106 | (1.47) | -0.02026 | -(0.25) |
| *Loser-Winner* | 0.354% | (3.36) | 0.08135 | (1.05) | 0.06818 | (0.39) | 0.01652 | (0.16) |
| **Generic Strategy** | α | *t* | β | *t* | γ | *t* | φ | *t* |
| H1 | | | | | | | | |
| *Loser* | 0.792% | (7.16) | 1.33991 | (11.70) | 0.15665 | (1.40) | -0.24097 | -(1.85) |
| *Winner* | -0.328% | -(3.87) | 0.94988 | (14.27) | 0.27279 | (2.84) | -0.28930 | -(2.59) |
| *Loser-Winner* | 1.120% | (7.73) | 0.39003 | (2.51) | -0.11614 | -(0.80) | 0.04833 | (0.27) |
| H2 | | | | | | | | |
| *Loser* | 0.576% | (5.72) | 1.20082 | (16.00) | 0.19192 | (1.80) | -0.32182 | -(2.63) |
| *Winner* | -0.174% | -(2.21) | 1.05797 | (21.51) | 0.15135 | (1.44) | -0.22863 | -(2.08) |
| *Loser-Winner* | 0.750% | (5.69) | 0.14286 | (1.56) | 0.04057 | (0.28) | -0.09319 | -(0.57) |
| H3 | | | | | | | | |
| *Loser* | 0.365% | (3.88) | 1.22348 | (21.02) | 0.34478 | (2.44) | -0.18339 | -(1.52) |
| *Winner* | -0.056% | -(0.61) | 1.13404 | (19.55) | 0.17973 | (1.74) | -0.20248 | -(1.54) |
| *Loser-Winner* | 0.420% | (3.12) | 0.08944 | (1.17) | 0.16505 | (0.91) | 0.01909 | (0.10) |

Table 7 illustrates intercept and factor loadings of the three factor model for the value-weighted portfolios using the Newey-West procedure of standard errors, generating t-statistics robust to autocorrelation and heteroscedasticity.

It seems that our findings are in line with Chan and Chen's (1991), namely that small and large firms have different sensitivities to risk factors and that this is important for pricing assets, but that in the case of the zero investment portfolios the size effect along with the value effect, remain statistically insignificant. In sum, we can confirm our second hypothesis. We find statistically significant abnormal profits across strategies in the Dow Jones STOXX 600. Most importantly, this illustrates that contrarian profits are not explained by the risk modelled for. However, we cannot reject that the zero investment strategies are subject to some market risk and that the sector neutral strategy does not neutralize the net beta exposure. It however persists to show slightly lower beta exposure vis-à-vis the generic strategy. From an investor's point of view it is questionable whether the difference in exposure is economically meaningful. As we have shown above an investor's profits are only partially explained by market exposure. It is true that both strategies to some extent are sensitive to movements in the market but it has become apparent that in order to explain contrarian profits and any differences between the strategies that one must extend the analysis.

### 5.4 Robustness to measurement errors and transaction costs

As pointed out in the literature (see Conrad and Kaul, 1993; Conrad, Kaul and Gultekin, 1997) contrarian profits can be spurious and sprung from measurement errors driven by the bid-ask spreads. Next we examine the sample's robustness to bid-ask bounce by using bid-to-bid prices instead of closing prices (see Antoniou, Galariotis and Spyrou, 2006). We expect bid-ask errors to have modest influence on our findings, due to the liquidity of the index at hand. However it is well recorded in the literature that the effect from these errors has material effect on weekly data. Our findings are reported in Table 8 below.

**Table 8: Bid Prices**

| Strategy | Bid Prices | | Closing Prices | |
|---|---|---|---|---|
| | Average | *t* | Average | *t* |
| Sector Neutral | | | | |
| *Loser-Winner* | 1.134% | (9.54) | 1.0392% | (9.06) |
| Generic | | | | |
| *Loser-Winner* | 1.109% | (7.17) | 0.9705% | (6.67) |

Table 8 illustrates contrarian profits using bid prices compared with equivalent data set of closing prices. This is based on a dataset with stocks with at least 40 observations per year from1997 and onward.

The bid-to-bid robustness tests were performed as follows. Bid prices were collected from Datastream. Since bid prices were not available for every week we set a constraint to securities with at least 40 observations every year.[9] With the reduced dataset on bid prices we also excluded observations prior to 1997 as the data availability significantly increased after 1996. Equivalent returns based on closing prices were also calculated for comparability.

Our robustness tests on bid prices had remarkable findings. The variability of the raw returns did not decrease for the bid prices compared to equivalent closing prices as suggested by Kaul and Nimalendran (1990) who find that bid-ask errors explain over 50% of the small firm variance while bid-ask errors explain over 23% of the large firm variance. In contrast to Antoniou, Galariotis and Spyrou (2006) our contrarian profits increased slightly and furthermore the variability did not decrease. The results are inconclusive; as the STOXX 600 consists of more actively traded securities the differences in volatility might explain some part of the findings of closing and bid prices. However the literature also shows contradictory results. Conrad, Kaul and Gultekin, (1997) find that the bid-ask bounce explains all profits in the NASDAQ while Jegadeesh and Titman (1995) disagree.

Next we investigate bid-ask spreads. Atkins and Dyl (1990) find on average bid-ask spreads of 3.57% for stocks with large price declines, which is much larger than the two-day abnormal return found for these stocks. Correspondingly the average bid-ask spread for the stocks with large one-day price increases were 3.29% overshadowing the price reversals related to these stocks. Thus we compare the bid-ask spread of prior winners and prior losers, presented in the Table 9 below.

[9] The range of 30, 35, 45 and 50 observations per year and security were also tested for but did not significantly alter the result.

**Table 9: Average Bid-Ask Spread**

| | Average | *t* |
|---|---|---|
| Sector Neutral Strategy | | |
| *Loser* | 0.675% | (34.94) |
| *Winner* | 0.624% | (38.20) |
| Generic Strategy | | |
| *Loser* | 0.788% | (41.03) |
| *Winner* | 0.708% | (46.00) |
| Total | 0.557% | (154.36) |

Table 9 illustrates the average bid-ask spread of the winner and loser portfolios across strategies

For the same dataset as the bid-to-bid investigation we estimated the bid-ask-spread for the different portfolios. As can be seen two patterns evolve. (1) Bid-ask-spreads are lower for winners. (2) The sector neutral strategy generally has a lower bid-ask spread.

Next, we estimated the return for an investor who places his money in the strategies over one holding week (H1) assuming no market impact or short-selling constraints. Based on closing prices in the formation week F he employs the sector neutral and the generic strategy. However the investor is constrained by bid-ask spreads imposed by the market maker.[10]

**Table 10: Contrarian return applying Bid-Ask spreads**

| | Average | *t* |
|---|---|---|
| Sector Neutral Strategy | | |
| *Loser-Winner* | -0.420% | (3.76) |
| Generic Strategy | | |
| *Loser-Winner* | -0.576% | - (3.40) |

Table 10 illustrates return for contrarian strategies when buying (selling) on ask (bid) prices.

The average returns of the contrarian strategies are reported in Table 10 above. The table shows that the investor on average gets a slightly negative return, after imposing bid-ask spreads on both strategies. This suggests that after taking transaction costs into consideration the profits disappear even in the absence of trading commission. With the data at hand and the methodology in use, we conclude that contrarian strategies are not robust to transaction costs in the form of bid-ask spreads, rejecting the third hypothesis.

[10] Long position: $\frac{BID_t}{ASK_{t-1}} - 1$, Short position: $\frac{ASK_t}{BID_{t-1}} - 1$

*5.5 Historical performance evaluation of the two strategies*

This far we have concluded that the contrarian profits an investor yields from both strategies only to some part are explained by market risk. Most of the profits are explained by transaction costs in the form of bid-ask spreads. A remedy for the bid-ask spreads would be to choose to employ the contrarian strategies on a selection of stocks with the lowest bid-ask spreads. This however raises the question if the observed contrarian profits would persist with stocks with lower bid-ask spreads. If so, and an investor can overcome the problem with transaction costs he will be interested in whether a reduced exposure to the industry effect would enhance overall portfolio performance. Figure 2 shows the one-year rolling average weekly return for the H1 portfolios across investment strategies. At any data point, the graph shows the average weekly return over the past 52 weeks.

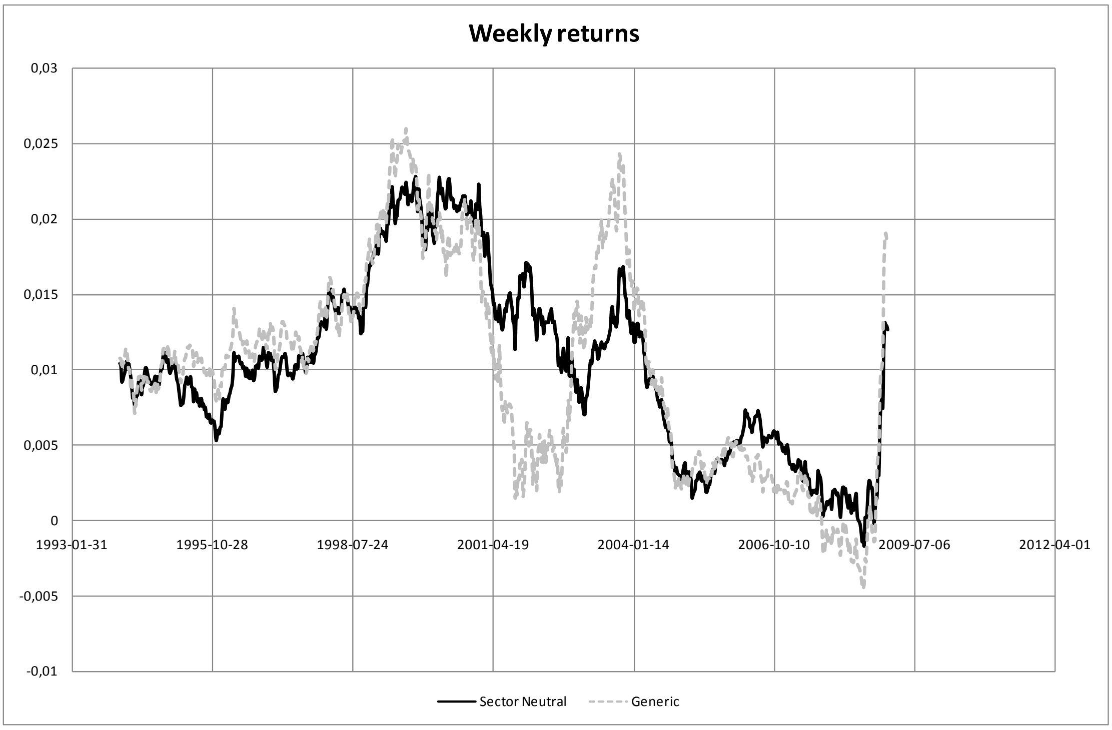


**Figure 2: Illustrates the one year rolling average weekly return for the H1 portfolios across contrarian strategies before controlling for bid-ask biases.**

The return series depicted in Figure 2, show a pattern consistent with our previous findings. By constructing a sector neutral strategy, one reduces the overall portfolio-risk of contrarian strategies. Next, we conduct a historical return to variability analysis (Sharpe measure), to validate our findings. As for the return series in Figure 2, we analyse the H1 zero investment portfolios. This is motivated by the fact that this period is the prime source of price reversals and thus the strategy that would be implemented by an investor. The return to variability analysis is a straightforward way of measuring the attractiveness of an investment portfolio by assessing the risk premium in relation to its standard deviation. The rationale behind the Sharpe measure is that investments typically entail accepting some risk in return for the prospect of earning more than the risk free rate of return.

Figure 3 depicts the rolling Sharpe measure for the return series outlined in Figure 2. Thus the graph shows the one-year rolling average weekly Sharpe measure, or put simply every data point in Figure 2 divided by the corresponding standard deviation of the time period. As a reference, the Sharpe ratio of the market portfolio is also depicted in the graph. Evidently, the sector neutral strategy predominantly exceeds the generic strategy in terms of return to variability, with an average Sharpe ratio of 0.42 versus 0.33 for the generic portfolio over the time period. Within the framework of our methodology, we conclude that the sector neutral strategy historically is more efficient than the generic strategy, confirming our fourth hypothesis. Before imposing transaction costs on the contrarian strategies the return to variability payoff in relation to the market portfolio indicates that there is value added in pursuing contrarian profits for an investor.

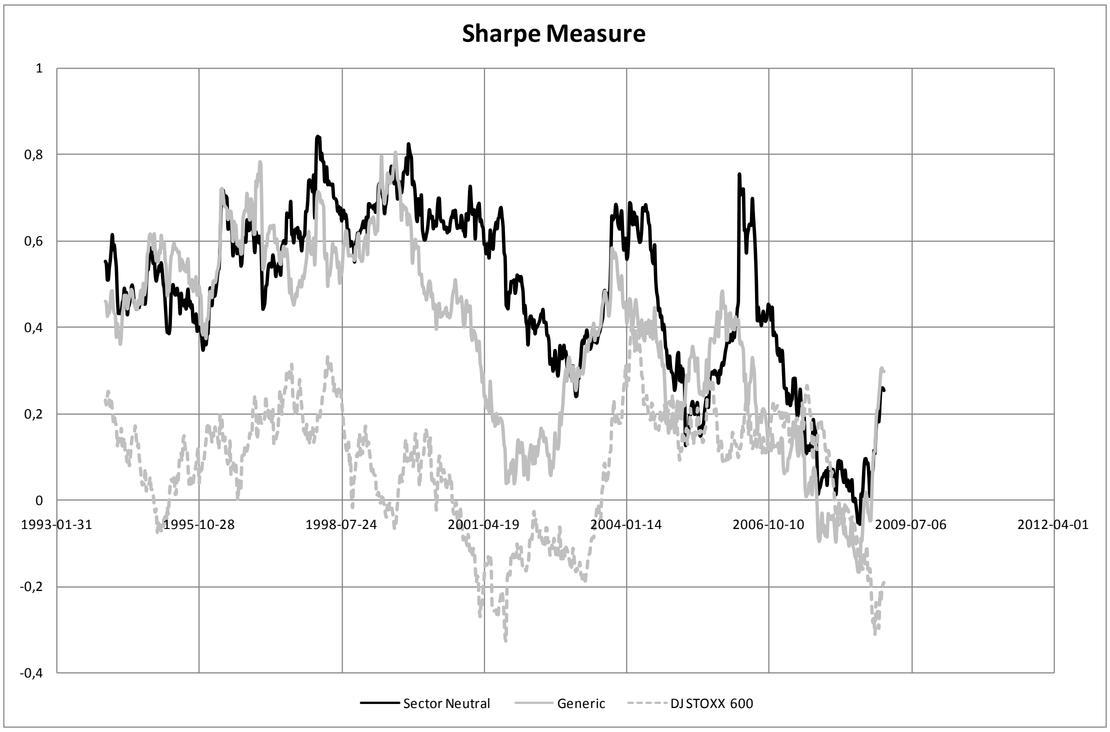


**Figure 3: Illustrates the rolling Sharpe measure for the one year average weekly returns.**

Figure 4 illustrates the cumulative returns an investor yields when reinvesting the weekly profits back into the contrarian strategies. When disregarding transaction costs in the form of bid-ask spreads the market return is dwarfed in comparison to the contrarian strategies. However when an investor is forced to buy at the ask price and sell at the bid price the market portfolio becomes a far better investment choice.

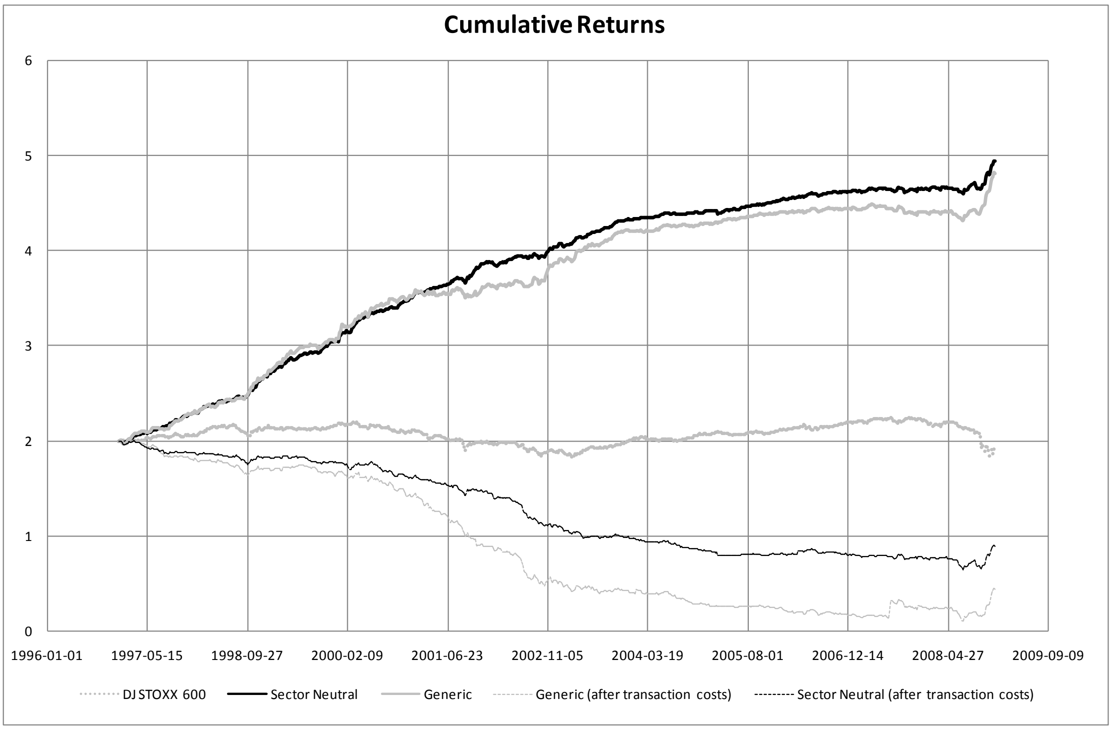


**Figure 4: illustrates the cumulative returns of the sector neutral and generic strategy. The results are shown using logarithm with base 10.**

## 6. Summary and Concluding Remarks

In this paper, we examine weekly stock return behaviour on the Dow Jones STOXX 600 between January 1993 and December 2008. We construct two equally-weighted zero investment contrarian strategies where one is exposed to industry effects and one has a reduced exposure to industry effects. We name them the *generic strategy* and the *sector neutral strategy.* The sector neutral strategy (the generic strategy) is created by drawing the extreme winners and extreme losers within each sector (over the full universe of stocks) from a preceding formation week, F, and placing them in separate portfolios. These portfolios are held over holding periods corresponding to one, two and three weeks after formation H1, H2 and H3 respectively. Next, we create a zero investment portfolio for each holding period by subtracting the average return of the winner portfolio from the average return of the loser portfolio.

Next, we investigate four hypotheses. Namely, whether (1) a *sector neutral strategy* and a *generic strategy* generate statistically significant positive raw returns. (2) Whether a *sector neutral strategy* and a *generic strategy* generate statistically significant positive risk-adjusted returns. (3) Whether a *sector neutral strategy* and a *generic strategy* generate statistically significant positive returns robust to measurement errors and transaction costs caused by bid-ask spreads. (4) Whether a *sector neutral strategy* is superior to a *generic strategy* in terms of historical return to variability, suggesting that industry effects have an impact on portfolio risk.

Firstly, we find that contrarian profits are of material magnitude and statistically significant for both the generic and the sector neutral strategy on the Dow Jones STOXX 600, and primarily captured in the first week following formation. An investor employing a contrarian strategy has yielded an annualised return of 56% on average, outperforming the corresponding annualised 7% return realised by holding the market portfolio. For the sector neutral strategy this is achieved at a slightly lower standard deviation than the market portfolio. Due to the selection algorithm of both contrarian strategies, both strategies are extremely active, reinvesting 93% of the capital into new stocks weekly, indicating that both strategies incur large transaction costs.

Secondly, when applying the CAPM we find a distinct pattern. (1) The generic strategy's winner and loser portfolios generate slightly higher beta than the sector neutral strategy. (2) Losers are riskier than winners. (3) This asymmetry generates a significant beta exposure for zero investment portfolio in H1. (4) The asymmetry is slightly larger for the generic strategy in H1 vis-à-vis the sector neutral portfolio, whilst in H2 and H3 the opposite holds. Most important abnormal profits prove persistent when accounting for market risk. When applying the 3FM we find that none of the SMB and HML slope coefficients proves statistically significant for the zero investment portfolios across strategies and holding periods suggesting that neither strategy is exposed to the risk associated with firm size and value. The beta coefficient still proves statistically significant in H1 across strategies. In all we find statistically significant abnormal profits across strategies in the Dow Jones STOXX 600, which illustrates that contrarian profits are not explained by the risk modelled for. This is an intuitive result as the returns of the contrarian strategies are so materially different from the factors. In order to explain these profits the strategies would need to have an unrealistic net exposure to these factors. For an investor employing a contrarian strategy this indicates that a major part of the returns can be earned free from the systematic risk of the market. However we cannot reject that the zero investment strategies are subject to some market risk. Since the contrarian profits are of material magnitude into consideration we argue that the noise induced by a currency effect would have modest impact on the economic significance of our findings. If one in particular wishes to control for the currency effect in future studies, we suggest taking on a smaller sample restricted to Euro zone members.

Thirdly, when investigating the robustness to measurement errors and transaction costs there are important implications to our findings. By using bid-to-bid prices we find that the returns are robust to bid-ask bounces. The negative serial correlation introduced by Roll (1984), inflicted by bid-ask bounces do not explain the contrarian profits. If we impose transaction costs in the form of bid ask spreads, the results are altered. When exposing the contrarian strategies to the constraints an investor faces in the form of bid-ask spreads, the strategies yield, on average slightly negative returns. These results are also before taking other transaction costs such as trading commissions into consideration. With the data at hand and the methodology in use, we conclude that contrarian strategies are not robust to transaction costs.

Finally the sector neutral strategy predominantly exceeds the generic strategy in terms of return to variability. Thus within the framework of our methodology, we conclude that the sector neutral strategy historically is more efficient than the generic strategy, and industry effects have an impact on portfolio risk. We conclude that more homogeneous pair-trades reduce the variability in the returns without offsetting the contrarian profits significantly. Asness, Porter, and Stevens (2000) elaborate on the advantages of pursuing sector neutrality. Firstly a firm's risk and the related ability to earn economic rents could reasonably be a function of the firm's position within its industry rather than its position relative to all firms in the economy. For a contrarian strategist this indicates more homogenous pair-trades. Secondly, as we have seen in our paper, intra-industry contrarian strategies are by construction highly diversified across industries. In this context, both strategies show a higher return to variability in relation to the market portfolio. However our methodology does not explicitly provide evidence on whether industry momentum exists in the short-term and if present whether our strategy would counterbalance this.

Relating to what has been said our results from the Dow Jones STOXX 600 indicate that contrarian strategies are present in the European market, and not driven by the systematic risk modelled for. These findings contribute to the empirical support found in other markets. Despite different methodologies it is interesting to compare average weekly returns across markets. Our weekly average contrarian profits are proximately 1.08% for both strategies in comparison to the 1.02% for the UK (Antoniou, Galariotis and Spyrou, 2006) and 1.37% for the US (Jegadeesh and Titman, 1995). These findings, namely that short-term contrarian strategies yield abnormal returns have often been interpreted in the literature as support for significant stock price overreaction to firm specific information. While others (Lo and MacKinlay, 1990) argue that these profits primarily are a result of some stocks reacting quicker to information than others. Campbell, Grossman, and Wang (1993) point at the price pressure generated by liquidity motivated trades as an explanation for price reversals. No matter the source of these profits our findings indicate, in line with the literature (e.g. Jegadeesh and Titman, 1995; Antoniou, Galariotis and Spyrou, 2006 and Ni, Lui and Kang, 2002) that price reversals are robust to measurement errors, at least within the framework of the bid-ask bounce. Like Atkins and Dyl (1990), our profits are dwarfed by the transaction costs in the form of bid-ask spreads. We suggest in line with Antoniou, Galariotis and Spyrou (2006) that a potential remedy would be to construct portfolios based on large stocks with small bid-ask spreads.

The finding suggests that there are topics of interest for further research. Namely, to further investigate the possibility to construct more sophisticated contrarian trading strategies, and to see how their profits relate to a generic strategy in terms of magnitude and the variability of these profits. More importantly, our findings suggest that transaction cost have material impact on contrarian profits. Overcoming this obstacle by changing methodology or applying contrarian strategies on the markets with the smallest bid-ask spread would add value to debate on the economic significance of contrarian profits, benefiting both academics and investors.

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# 8. Appendices

## *Appendix 1 Industry Classification Benchmark (ICB)*

Industry Classification Benchmark (ICB) is a straightforward four-tier structure developed by Dow Jones and FTSE that is structured similarly to the former Dow Jones Global Classification Standard (DJGCS). On the $20^{th}$ of September 2004 Dow Jones STOXX 600 switched sector classifications from DJGCS to the ICB.

In the ICB (formerly DJGCS), every company is classified on four levels according to the breakdown of activities generating their gross revenue. The structure is as follows: firstly 10 *Industries* (formerly 10 *Economic Sectors*), secondly 18*Supersectors*(formerly 18 *Market Sectors*), thirdly 41 *Sectors* (formerly 51 *Industry Groups*) and finally 114*Subsectors*(formerly 89 *Subgroups*).

This paper employs the *Supersector* classification to the data. This is motivated by (1) wide enough definition to incorporate enough index constituents in its grouping to allow for pair-trades over the time series and (2) the classification is more homogenous in relation to the former DJGCS classification providing continuity in the portfolio formation process.

The conversion rule from *Market Sectors* to *Supersectors* has been as follows; firstly on the corresponding *Subgroups*, secondly on the corresponding *Industry Groups* and thirdly on the corresponding *Market Sectors*. The *Supersectors* are defined on the next page:

**Table 1.1: Number of Constituents in sample classifed in accordance with ICB**

| Sector | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | **Total** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Oil & Gas (0500)* | 10 | 10 | 11 | 12 | 14 | 16 | 16 | 10 | 12 | 13 | 11 | 10 | 12 | 15 | 23 | 25 | **220** |
| *Chemicals (1300)* | 12 | 14 | 17 | 17 | 18 | 18 | 18 | 12 | 11 | 12 | 12 | 14 | 15 | 15 | 15 | 16 | **236** |
| *Basic Resources (1700)* | 11 | 14 | 19 | 19 | 24 | 29 | 28 | 15 | 11 | 11 | 11 | 16 | 14 | 17 | 19 | 23 | **281** |
| *Construction & Materials (2300)* | 26 | 27 | 29 | 30 | 33 | 35 | 33 | 28 | 18 | 24 | 22 | 22 | 27 | 25 | 26 | 26 | **431** |
| *Industrial Goods & Services (2700)* | 38 | 37 | 37 | 39 | 46 | 49 | 60 | 47 | 59 | 69 | 61 | 57 | 52 | 53 | 54 | 65 | **823** |
| *Automobiles & Parts (3300)* | 9 | 9 | 9 | 9 | 11 | 11 | 13 | 13 | 11 | 10 | 10 | 11 | 12 | 13 | 12 | 13 | **176** |
| *Food & Beverage (3500)* | 20 | 20 | 22 | 22 | 22 | 22 | 21 | 16 | 15 | 15 | 18 | 18 | 18 | 18 | 18 | 16 | **301** |
| *Personal & Household Goods (3700)* | 11 | 11 | 11 | 11 | 13 | 16 | 20 | 20 | 23 | 22 | 21 | 25 | 29 | 26 | 28 | 24 | **311** |
| *Health Care (4500)* | 5 | 6 | 6 | 8 | 8 | 9 | 12 | 16 | 23 | 31 | 25 | 23 | 22 | 21 | 17 | 17 | **249** |
| *Retail (5300)* | 6 | 5 | 8 | 8 | 11 | 15 | 13 | 12 | 13 | 17 | 19 | 16 | 18 | 16 | 16 | 17 | **210** |
| *Media (5500)* | 4 | 5 | 7 | 7 | 8 | 9 | 11 | 22 | 33 | 28 | 23 | 23 | 27 | 30 | 26 | 24 | **287** |
| *Travel & Leisure (5700)* | 19 | 21 | 21 | 21 | 29 | 28 | 32 | 25 | 24 | 26 | 30 | 31 | 18 | 17 | 15 | 17 | **374** |
| *Telecommunications (6500)* | | | | | | | | | 24 | 23 | 18 | 18 | 18 | 17 | 16 | 15 | **149** |
| *Utilities (7500)* | 15 | 15 | 15 | 15 | 16 | 16 | 17 | 23 | 16 | 19 | 14 | 17 | 17 | 20 | 24 | 23 | **282** |
| *Banks (8300)* | 27 | 28 | 31 | 33 | 35 | 36 | 43 | 56 | 49 | 52 | 51 | 53 | 50 | 50 | 48 | 44 | **686** |
| *Insurance (8500)* | 16 | 17 | 19 | 21 | 26 | 30 | 38 | 47 | 28 | 29 | 25 | 26 | 27 | 27 | 26 | 24 | **426** |
| *Financial Services (8700)* | 21 | 22 | 24 | 26 | 29 | 26 | 27 | 29 | 20 | 30 | 29 | 24 | 26 | 29 | 34 | 33 | **429** |
| *Technology (9500)* | 10 | 10 | 10 | 12 | 14 | 13 | 19 | 26 | 22 | 30 | 27 | 24 | 23 | 22 | 21 | 21 | **304** |
| **Total** | **260** | **271** | **296** | **310** | **357** | **378** | **421** | **417** | **412** | **461** | **427** | **428** | **425** | **431** | **438** | **443** | **6175** |

Table 1.1 illustrates the number of constituents over year and sector. ICB supersector codes are shown in paranthesis.

*Appendix 2 Testing the neutrality of the "sector neutral" strategy*

If a strategy is strictly neutral, then it has a zero net exposure to the systematic risk of the underlying index. With pair-trade portfolios of stocks within the same sector we dampen the systematic risk exposure towards that sector. If this match is perfect, the systematic risk disappears. Thus in order to test the level of neutrality, we regress the return series of pair-trades towards the return series of the sector the pair of stocks belong to. If our pair-trades generate strict neutrality towards its sector index, the slope coefficient should be zero. The results are reported below.

**Table 2.1 Testing the neutrality of "the sector neutral" strategy**

| Sector | Coef. | t-stat | R-square | Std.Err | Average No. Stocks |
|---|---|---|---|---|---|
| *Oil & Gas (0500)* | 0.20492 | (3.11) | 0.0115 | 0.06592 | 14 |
| *Chemicals (1300)* | 0.24489 | (3.45) | 0.0141 | 0.07088 | 15 |
| *Basic Resources (1700)* | 0.04589 | (0.75) | 0.0007 | 0.06130 | 18 |
| *Construction & Materials (2300)* | 0.30179 | (3.38) | 0.0135 | 0.08935 | 27 |
| *Industrial Goods & Services (2700)* | 0.15928 | (1.54) | 0.0028 | 0.10332 | 51 |
| *Automobiles & Parts (3300)* | 0.53191 | (9.60) | 0.0997 | 0.05540 | 11 |
| *Food & Beverage (3500)* | 0.31518 | (2.85) | 0.0096 | 0.11074 | 19 |
| *Personal & Household Goods (3700)* | 0.31079 | (3.20) | 0.0121 | 0.09716 | 19 |
| *Health Care (4500)* | 0.30329 | (2.68) | 0.0086 | 0.11296 | 16 |
| *Retail (5300)* | 0.03832 | (0.38) | 0.0002 | 0.10062 | 13 |
| *Media (5500)* | 0.30310 | (3.24) | 0.0124 | 0.09364 | 18 |
| *Travel & Leisure (5700)* | 0.18489 | (1.85) | 0.0041 | 0.09991 | 23 |
| *Telecommunications (6500)* | 0.51752 | (3.61) | 0.0305 | 0.14348 | 19 |
| *Utilities (7500)* | 0.49599 | (4.55) | 0.0243 | 0.10904 | 18 |
| *Banks (8300)* | 0.04708 | (0.46) | 0.0003 | 0.10320 | 43 |
| *Insurance (8500)* | -0.00329 | -(0.04) | 0.0000 | 0.08924 | 27 |
| *Financial Services (8700)* | -0.07995 | -(0.68) | 0.0005 | 0.11838 | 27 |
| *Technology (9500)* | 0.28583 | (3.37) | 0.0135 | 0.08480 | 19 |

The table shows the estimates of the regression of the return series of pair-trades towards the return series of the sector the pair of stocks belong to

We find that all pair-trades of stocks in a certain sector generate coefficients lower than 1 towards the sector index they belong to. The magnitude of the coefficient is on average 0.2337 across sectors. Economically this indicates that if a sector moves by 1% in either direction, the sector neutral strategy on average moves in the same direction by 0.23 %. We conclude that the pair-trades of the sector neutral strategy have material effect on the exposure to systematic risk of the sectors. The capability of the strategy to neutralize systematic risk varies widely over sectors. For example Basic Resources, Banks, Insurance and Financial Services generate a systematic risk exposure statistically indifferent from zero. While for example Automobiles & Parts, Telecommunications, Chemicals and construction & Materials, frequently generates a material systematic risk exposure. In all it is clear that the strategy is far from neutral, but for a comparable analysis of whether a sector neutralized strategy render benefits in return to variability vis-à-vis a fully exposed strategy, we argue it will be sufficient enough for the purpose of this study.