S&P Global Sector Survivals:

Momentum Effects in sector indices underlying iShares

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Abstract

This study investigates survival of the momentum effects in S&P Global 1200 sector index returns which are underlying indices for iShares, by employing a methodology which allows analyzing the momentum effect without being dependant on zero-investment portfolios. We design a trading strategy based on momentum survival time for ten S&P Global 1200 sectors and show that for most of the sectors, long, short and long/short momentum strategies are profitable at the realistic level of transaction costs, generating substantially higher Sharpe ratios than buy-and-hold sector index strategy.

Key words: Momentum survival, Kaplan-Meyer estimator, Transaction costs

JEL code: G14, G11

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I. Introduction

Trading on momentum has become an integral part of portfolio and asset management. Reasons for the huge success of this concept lie not only in its simplicity, but also in the way how market participants behave. An upward or downward trending stock price always teases the eye to extrapolate. Concepts such as overconfidence of private over public information (Daniel, Hirshleifer and Subrahmanyam, (1998, 2001)), or optimism and wishful thinking, as well as representativeness and conservatism, in terms of underweighting new information relative to prior (Barberis, Shieifer and Vishny, (1998)), are causing peoples' expectations to deviate from Von Neumann and Morgenstern's (1947) expected utility theory. Above observations have lead to the academic concept of limited arbitrage, which states that irrationality can have a substantial and long-lived impact on prices, which cannot be undone by arbitrage. Based on this consideration a wide range of behavioral trading strategies such as Put/Call indices and Confidence Indices have been introduced. It has often been argued that momentum trading is the least favorable amongst behavioral trading strategies, as it not only runs counter to common sense "buy low, sell high"[2], but also as it is vulnerable to volatility in markets. Key to profitability of momentum trading is to spot trends early and to react quickly. For this reason it becomes evident why leading financial institutions spend considerable amounts of time researching this phenomenon. The distinction between trends that will last from trends that will not last, might well be a trader's comparative edge in the hunt for Alphas.

[2] By definition, momentum trading means that you will not buy your stocks at their lowest, nor will you sell them at their highest.

Central aim of this study is to provide an econometric model which allows to identify potentials for momentum trading and to assess their feasibility. The presented model is based on the analysis of different industrial sectors which are used as the underlying sector indices for S&P Global 1200 iShares. The analysis can be applied to any other index underlying an Exchange Traded Fund.

Momentum as an academic concept, had its breakthrough with the study by Jegadeesh and Titman (1993). Results of the study suggest that short and long holding periods show mean reversion of momentum returns, whereas mid term holding periods lead to positive and highly significant momentum returns. Since Jegadeesh and Titman's study, a large body of academic research has supported evidence on medium-term stock price continuations. Namely, Rouwenhorst (1998) has identified momentum effects for 12 European countries and US over a period of 1978-1995.

The general problem of the studies, which use the no arbitrage argument to identify momentum effects, is the construction of the zero-investment portfolios. The zero-investment portfolio invests an equal dollar amount in long and short positions. However, this is not a market neutral portfolio, which would have required that long position's market sensitivity (beta) with the short position's market sensitivity (beta) are balanced out. The advantage of such a portfolio is that it would have virtually eliminated market risk. This would represent an appropriate zero arbitrage portfolio. Jegadeesh and Titman (1993) find the market capitalization of the loser portfolio to be on average smaller than the market capitalization of the winner portfolio, implying a style tilt. Furthermore winner and loser portfolios show different market betas, suggesting different systematic risk profiles, implying no zero arbitrage portfolios. In Grinblatt and Moskowitz (2003) this style tilt is investigated and their findings suggest that a significant part of momentum returns stems from short positions in small and illiquid stocks and significant November short positions due to anticipation of tax loss selling in December. Lesmond, Schill, and Zhou (2003) support the argument that most of momentum profitability can be explained by frequent trading on high-cost securities. Hong, Lim and Stein (2000) find a significantly negative relation between information flow and momentum; supporting the findings above and suggesting a link between analyst coverage, momentum and market efficiency. Grundy and Martin (2001), however, find that not all of the momentum profitability is explained by cross sectional variability in returns, therefore it might well be argued that a common momentum factor exists, being coherent with the findings of Rouwenhorst (1998).

Generally, findings suggest a high sensitivity of momentum returns to transaction cost, which represent a crucial problem of momentum analysis. Carhart (1997), for instance, concludes that momentum is not exploitable after transaction costs are taken into account. Consequently, several attempts have been undertaken to increase the feasibility of momentum returns, such as restricting the sample to large caps only (Chan, Jegadeesh, and Lakonishok (1999)), or neglecting short positions (Grinblatt and Moskowitz (2003)), or even more interestingly, by applying option-based implementations of momentum strategies (Rey, (2004)).

In contrast to the majority of previous research, this paper applies an alternative approach to identifying and quantifying momentum effects. It will closely follow the model introduced in Jochum (2000), which investigates momentum effects by constructing economic survivorship curves[3]. Namely, the KAPLAN-MEIER estimator (Kaplan and Meier, (1958)) allows measuring to an extent in which an existing trend will persist beyond the present day. Clear advantage of this model over the Jegadeesh and Titman (1993) approach is the circumvention of problems attached to the zero-investment portfolio. Further, the model allows shedding a light on momentum effects from a trader's perspective, rather than a portfolio manager's perspective. We will establish a trading rule based on daily data of ten S&P Global 1200 sector indices which are used as underlying for iShares, allowing the identification of positive or negative return sequentials, representing momentum effects. By applying survivorship curves a probability model for the survival rates of these return sequentials can be built. Benchmark simulations for sector survival curves then allow the identification of momentum effects.

II. Data and Methodology

A. Description of Data

For the empirical validation of the model we use closing daily prices of ten S&P Global 1200 Sector indices for 10 sectors which are used as the underlying indices for ETFs, in particular iShares. Tracking S&P Global 1200 Sector indices with index tracking portfolios would be also possible, however more expensive and incurring greater tracking errors than iShares. The availability, unrestricted possibility of short-selling and low transaction costs associated with trading of iShares are making this strategy feasible for the real world investor. For example, the iShares S&P Global Energy Sector Index fund seeks investment results that correspond generally to the price and yield performance, before fees and expenses, of the S&P Global 1200 Energy Sector Index. The sectors we use are namely:

[3] For a survey of economic survival and hazard functions, see Kiefer (1988).

Consumer Discretionary Sector, Consumer Staples Sector, Energy, Financials, Healthcare, Industrials, Technology, Materials, Telecommunications and Utilities Sector. The sample spans from 1st January 1998 to 6th December 2006 allowing the analysis of 2330 data points. We base this analysis on the idea that sector benefits vary across stages of economic cycles, we might find that the return generating process moves independently across sectors.

In Section III price index data will be used, as this allows the unbiased comparison of empirical curves to the theoretical benchmark curves[4]. In Section IV, however, we will also be employing total return index, which incorporates dividend reinvestment and is adjusted for capitalization changes. Hence, it represents the appropriate decision basis for a trader.

B. Defining the momentum signal

The initial step to defining momentum survivorship curves is to formalize a momentum signal. We, therefore, base our signal on a technical trading rule. The definition of the trading strategy can hereby be arbitrarily chosen as long as it is applied to both, the empirical series and the simulations. We identify a momentum signal when in two consecutive periods a positive return is realised, giving us a purchase signal for positive momentum sequentials and a sell signal for negative momentum sequentials, respectively, as illustrated in Table 1.

- Insert Table 1 -

[4] We will not be considering dividend reinvestments in the survivorship analysis, because theoretical benchmark models do not capture this information.

Once the momentum signal is formed, we can define Survivorship and Hazard curves. Those curves are primarily used in Cancer research to investigate the effectiveness of medical treatment on patient groups. Earliest and most quoted study is for instance the paper of Kaplan and Meier (1958), followed by studies such as Kiefer (1988), which apply the concept to economic problems, such as the analysis of unemployment rates or estimation of credit default rates.

C. The Survivorship Estimator

Fundamental idea of survival functions is to model a probability curve for the survival rate of a sample. The target is the estimation of a time span in which an observation is 'alive'. This cannot be estimated in a single point of time, as the start, end and duration of the signal is unordered (uncensored) within the sample.

In this study, however, we will focus on survivorship probabilities, as this best captures the intuition behind the financial concept of momentum. Survival functions can either be estimated by non-parametric or parametric methods. Under the nonparametric specification, no assumptions about distributional characters of the survivorship curve have to be made. This allows a very high degree of flexibility. The KAPLAN-MEIER estimator hereby represents the standard method. By applying the KAPLAN-MEIER estimator, momentum observations can be ordered according to their duration and a probability of survival can be defined, therefore the KAPLAN-MEIER estimator represents the censored generalization of the empirical distribution function. By censoring, we mean that every observation has the same starting point. The theoretical construction of the KAPLAN-MEIER estimator can be made as follows. The probability of the survival function describes the probability that an observation is 'alive' after t periods. The survival function at time t can be calculated as:

$$\hat{S}(t) = \prod_{j:t(j)\leq t} \left(1 - \frac{d_j}{n_j}\right) \tag{1}$$

Where t(j) denotes the ordered failures at times t=t(j): t(1)≤ t(2) ≤ t(k), d_j represents the number of failures at time t=t(j). And n_j the number of items which are alive before t=t(j). Consequently the estimator takes the shape of a step function. Every step in the function then represents the change in probability of momentum surviving beyond a given time horizon t(j). The key fact is that the probability is conditional upon surviving, given that momentum is alive.

For purposes of illustration we use the information, given in Table 1. After momentum signals have been defined[5] they have to be ordered according to their length of appearance. The positive curve in Table 1 for instance, shows one time one momentum signal and one time two consecutive signals. This means that out of the two one period observations, one survives up to two periods. This is leading us to the conclusion that, providing one momentum signal has been observed, there is a 50% survival probability up to two consecutive periods. For the negative sample curve the initial survival probability for a two period survival is 0%.

[5] A momentum signal will throughout the analysis be defined as 1.

Precision of the estimates depends on the number observations; therefore, estimates for short momentum sequentials are more precise than for long momentum sequentials[6]. In order to make inferences the variance of the estimator is calculated as:

$$\mathrm{Var}\left(\hat{S}(t)\right)=\sum_{t(j)\leq t}\frac{d_j}{n_j(n_j-d_j)} \tag{2}$$

One central aim of the paper is to evaluate whether the empirical survivorship function does show pattern of momentum sequentials or not. For this reason we simulate benchmark processes for stock returns to get an idea of the dimension of a benchmark survival curve. Initial step for the implementation of the Monte-Carlo Simulation is to specify the formulation of the model, which will be used to generate the data. For this reason we define the Random Walk with drift and the ARMA(1,1) as appropriate benchmark processes. The Random Walk definition is based upon findings in the market efficiency literature[7]. The model defines the current price as a function of a constant, yesterday's price and a random term. A formal definition for the Random process is given in equation (3), where μ is the drift rate, P_{t-1} is the price in the previous period and u_t is a random term:

$$p_t=\mu+p_{t-1}+u_t \tag{3}$$

[6] because of small numbers of long momentum sequentials due to a high number of dropouts.

[7] For a thorough analysis of the Random Walk Hypothesis, see Campbell, Lo and MacKinlay (1997).

The definition of the ARMA (1,1) process as benchmark finds its justification in papers of Pagan (1996) and Fama and French (1988). Under the ARMA(1,1) specification returns rather than prices are modeled and the current return realization is a linear function of a constant, the previous return realizations, the previous equilibrium error and a random term. These models are highly appropriate for modeling short to medium term movements in stock returns, however they do not follow any underlying financial or economic theory. A formal definition for the ARMA(1,1) process is given in equation (4), where μ is the drift rate, y_{t-1} is the previous realization, u_{t-1} is the previous equilibrium error and u_t is the random term:

$$y_t = \mu + \phi_1 y_{t-1} + \vartheta_1 u_{t-1} + u_t \tag{4}$$

The second step of the Monte-Carlo Simulation includes the estimation of the parameters which define both processes. Parameter estimates are based on the sample starting from 1st January 1998 to 6th December 2006 including 2330 observations. In the simulation 10000 time series with exactly the same length as the empirical time series are produced. For every of the simulated time series we generate a survivorship curve. A simple t-test is applied to define the survival length of the simulated curves. To compare momentum survival rates we use mean survival times. Should the survival times of the empirical curves prove to be longer than for the benchmark simulations, we may conclude that the Random Walk Model and the ARMA(1,1) model do not capture the full complexity of the empirical price generating process.

This kind of momentum analysis has a clear advantage over traditional approaches to investigating momentum effects as it can be carried out using only one time series. This allows the analysis of single stocks, which would be not possible under the traditional specification. Further to this argument, the construction of survivorship curves helps to circumvent the problems associated with the zero arbitrage portfolios, as discussed in Section I.

III. Model estimation and evaluation

A stepwise calculation for the empirical KAPLAN-MEIER estimator for S&P Global 1200 Consume Discretionary Sector is given in Table 2.

- Insert Table 2 -

In the sample of 2330 daily return observations 650 positive two-day momentum signals have been identified. 368 positive return sequentials have been identified for three consecutive days, 11 for eight consecutive days and one up to eleven consecutive days. The number on negative two-day momentum signals identified for this index is 585. Maximum length of the negative momentum is slightly longer, 13 days. The KAPLAN-MEIER contribution rate and the Hazard rate can be interpreted as the periodical probability of a trend continuing or dying respectively. Both columns are inversely related and add up to 100%. The column of the KAPLAN-MEIER estimator shows the probability of survival beyond t(j) days conditioned upon the fact that momentum is alive in t(j). Following this interpretation, we find a 16% probability of a momentum survival beyond four days and a zero probability of momentum occurring longer than eleven days for the positive momentum effect. Results from Random Walk Monte-Carlo simulations, given in Table 3, suggest a slightly shorter momentum survival time of maximum nine days, while ARMA

(1, 1) Monte-Carlo suggests slightly longer maximum survival time of 13 days. The negative momentum is understated by the theoretical models. Table 2 results indicate that there is 9.74% probability that negative momentum will last longer than four days and no probability of momentum lasting longer than 13 days. The Monte-Carlo simulation results related to negative momentum from Table 3 show considerably shorter momentum survival times than eight days. This implies a less efficient market segment, which means that the theoretical models do not capture the empirical return-generating process.

- Insert Table 3 -

Similar results are found for all other S&P Global 1200 Sectors used in the analysis and their summary is presented in Table 10 in the Appendix.

In Table 4 mean survival times for all sectors are presented, which help in analyzing the pronouncedness of momentum effects across sectors. Firstly, results suggest that the Random Walk model underestimates empirical survivorship curves for positive momentum and often overestimates them for negative momentum. Consequently, it does not fully explain the observed price dynamics. For this reason it might well be concluded that the traditional efficient market hypothesis, suggesting the Random Walk as appropriate model, is not supported by the data. The ARMA(1,1) model shows the opposite results: it overestimates empirical survivorship curves for both positive and negative momentum in most of the cases. Certain sectors show considerably longer positive momentum empirical mean survival times than suggested by both models, such as Technology, Utilities, Financials and Industrials. On the other hand, Utilities, Financials, Materials and Consumer Discretionary Sector show greater discrepancy between empirical and theoretical negative momentum survival rate. Further to the findings above, we find that ARMA model explains positive momentum sequentials better than negative momentum sequentials. We also find that positive momentum sequentials live longer than negative sequentials, which is consistent with the findings of Jochum (2000).

- Insert Table 4 -

An indication as to why market momentum is stronger in an up-market than in a down-market, can be found in Grinblatt, Titman and Wermers (1995). They argue that fund managers tend to buy 'winning' stocks, but do not sell 'losing' stocks. This stronger tendency to buy upward moving securities reinforces positive market moves and thus creates positive market momentum. Generally, results suggest profit potentials, which have not been 'arbitraged' away. To evaluate the feasibility of these potentials we will implement a trading rule and assess the profitability of sector momentum trading.

IV. Trading Rule Implementation

Findings from the survivorship analysis in Section III suggest that the momentum effect survives on an average a little more than two days after it has been established. Therefore, we implement three trading strategies, namely long only, short only and long/short based on the following trading rules: 1) long only returns are generated by buying an index from the opening[8] of the day one and holding it to the close of day two following the positive momentum signal; 2) short only returns are generated by shorting an index at the opening price on the day following negative momentum signal and buying it back at a close of day two and 3) long/short strategy is a combination of long only and short only trading rule.

[8] Opening prices for S&P 1200 Global Sector Indices are available only since 2002. Given that in our trading strategies we want to capture both the bull and the bear market trend as in the theoretical modeling in Section III, we have backfilled the data to 1 January 1998 by extrapolating the prices as follows: taking the average percentage difference between the live opening and closing prices from 2002 onwards we adjust the closing prices prior to 2002 for that difference. Any outliers in the data have been excluded.

The borrowing rates we assume while short S&P Global 1200 sector indices are given in Table 5[9].

-Insert Table 5-

If we do not receive a positive (negative) momentum signal in the long only (short only) strategy, we assume investment in the cash index, namely the JP Morgan Global Cash Index (3 months). On the average, we are long (short) around 50% (remaining 50%) of the time in our sample period, the exact percentage slightly varies for each specific index. In the long/short strategy the sample is either long or short, so no investment in the cash index is needed. The existence of sector ETFs, in particular iShares on S&P Global 1200 Sectors, enables investors to apply trading strategies that we describe in reality, relatively cheaply.

Table 6 shows the annualized returns[10], standard deviations and Sharpe ratios of buy-and-hold Price index or Total Returns index for our long only, short only and long short momentum strategies.

- Insert Table 6-

It can be seen across the board for all indices that with the exception of some short strategies, the three momentum strategies produce much higher returns and similar standard deviation the buy-and-hold strategies. This automatically, implies substantially higher Sharpe ratios, particularly for long only and long/short momentum strategy. It appears from this part of the analysis that all three of our strategies are highly profitable when no transaction costs are taken into account. Inclusion of dividend income in the Total Returns

[9] Borrowing rates for S&P 1200 Global Sector iShares obtained from Baring Asset Management

[10] Calculated as Annualized holding period return assuming 252 trading days per year:

$$\left(\sqrt[no.of\,observations]{\frac{End\,of\,Period\,Value}{Start\,Value}}-1\right)\times 252$$

index increases returns of buy-and-hold and positive momentum strategy, while it actually has the opposite impact on the negative momentum one, but the overall long/short returns are increased. The Sharpe ratios are not significantly influenced by this inclusion of dividends.

To assess the economic effect of investing in our strategies, we calculate the end of period value of the initial investment of $100 in each of our strategies. The results from Table 7 suggest that, when no transaction costs are taken into account, both long only and long short strategies generate significantly greater end of period values that the buy and hold index strategy. Short strategy based on negative momentum is somewhat less successful, generating end of period values lower than the buy and hold strategy for five out of ten price indices and six out of ten total returns indices.

- Insert Table 7-

Nevertheless, one should not forget the importance that transaction costs play in determining the profitability of active strategies, particularly those active strategies based on frequent trading, such as the ones presented in this paper. Therefore, break-even transaction costs per trade are incorporated into the model, which allows analyzing the extent to which findings from the survivorship analysis can be arbitraged. Not only does this allow us to evaluate the overall level of profitability and feasibility of these strategies, but also the variations of break even points over different sectors.

Table 8 shows the breakeven value of transaction costs for the positive (long), negative (short) and long/short momentum trading strategy are shown. Break even values are calculated using buy and hold sector index strategy for each individual sector index. We optimize break-even transaction costs in three different ways: 1) with respect to the end of period buy and hold S&P Global 1200 Sector index value; 2) with respect to the coefficient of variation of the buy and hold strategy and 3) with respect to the Sharpe ratio of the buy and hold. Although the returns and end of period values following our momentum strategies are high, these returns are associated with a very high number of transactions, hence transaction costs become the crucial point to decide whether the strategy is profitable or not.

Results in Table 8, Panel A are based on Price Index and in Panel B on Total Returns Index data. The latter corresponds to the returns of iShares.

- Insert Table 8 –

Since dividends become a crucial point in determining the profitability of momentum effects, as they contribute to the annual performance of sector indices in the range of 0.84% to 3.479%, the threshold levels based on total return indices would be the appropriate decision basis for a trader. If we compare the results in Panel A with the results in Panel B of Table 8, it becomes strikingly clear that the threshold levels for the strategy based on both price index and total returns index are higher for positive momentum strategy for most indices than for the remaining two strategies. Additionally, whether dividends are used or not, does not dramatically change the level of breakeven transaction costs. Given this information, it becomes evident that dividends do not have a significant impact when it comes to defining the borderline of profitability. Furthermore, there is only a slight difference in the level of breakeven transaction costs with regards to the method of optimization used. Break-even transaction costs which equalize the end of period value of our trading strategy with the buy and hold strategy are the highest.

How realistic are the transaction costs that make our trading strategy profitable for different sectors? The transactions cost levels for algorithmic trading on the New York Stock Exchange lie in a range between 8 and 11 basis points (bps)[11]. For most of our sectors, the level of transaction costs for our positive momentum strategies is between 10 to 20 basis points per trade. iShares S&P Global Sectors expense ratio is between 0.48% and 0.65% p.a. which is equivalent to $96 per year for $20000 investment, which is highly feasible. In particular, for positive momentum strategy break-even transaction costs based on all three methods in Table 8 are greater than 8bps for all but three sectors (S&P Global 1200 Consumer Staples, Health Care and Utility), both for Price Index and Total Returns Index data. Single sectors such as Energy Services and Information Technology show considerable arbitrage opportunities. However, it can be noted that negative momentum strategies are less profitable as only four out of ten sectors is profitable according to all three methods of optimization for price indices, while only three out of ten sectors exhibits profitability when return indices are used. The profitability of the long/short strategy is highly influenced by the poor success of negative momentum strategy, i.e. by the losses on the short position, so similarly to short strategy only four (three) out if ten sectors based on price index (total returns index) have breakeven transaction costs greater than 8bps. We believe that the reason for less profitable performance of long only and long/short strategy is the borrowing costs when shorting as well as large number of trades. This implies that only long/short strategies that generate 8-10 times greater end of period wealth than buy and hold strategy can be profitable at a feasible level of transaction costs.

[11] Report Elkins/McSherry LLC, May 2005

Lastly, it is important to assess whether there is a positive relationship between survival rates and transaction cost thresholds. The most general problem of survivorship analysis is the fact that it only identifies the signal of a positive or negative return sequential, but it does not state anything about the level of return realizations. This implies that a sector with considerably short survival rates might well outperform a sector with long survival, if level of return realizations is high enough. This problem is catered for in the implementation of our trading rule.

Positive return realizations on two consecutive days represent one momentum observation. This momentum observation represents the buy signal for the trading strategy. After day two, the momentum effect survives on an average one to one and a half days more, before it dies away. The holding period for the trading strategy is exactly two days after a momentum signal has been received, as explained in greater detail at the beginning of this section. This implies that in terms of survival times we allow for a certain loss, which should vary according to the empirical mean survival times. Therefore a sector with a momentum effect which lives on an average for 2.1 days should perform worse than a sector with a momentum effect which lives on an average of 2.4 days.

In light of this discussion, we rank the sector strategies according to their survival times as well as threshold levels. This enables us to evaluate, whether there is a relationship between survival times and profitability of momentum returns. If the results suggest a positive relationship, and if the strategies prove to be profitable after accounting for transaction costs, the model might well be seen as an appropriate tool for making investment decisions.

- Insert Table 9 -

In Table 9 a ranking scheme of sectors according to different aspects is shown. The objective is to assess whether the ‘best’ sectors in terms of survivorship analysis are also the ‘best’ sectors in terms of transaction cost threshold. Column 1 shows the ranking according to break even transaction costs based on end of period value optimization, where the highest threshold receives the rank one and so on. Column 2 shows the ranking according to absolute survival time and columns 3 and 4 show rankings according to relative survival times. Relative rankings are defined as difference between the empirical mean survival times and mean survival times suggested by the simulations. Column 5 shows a relative ranking according to the empirical survival time and the average of combined survival times. As an example, the results for long momentum strategy for Financials Sector show that it is ranked the third in terms of transaction costs threshold and in terms differences between empirical and theoretical survival times. For short momentum strategy, Materials sector is ranked as number one in terms of threshold of transaction costs and empirical survival time, but is ranked as number two according to differences between empirical and theoretical survival times.

Our results overall suggest a certain degree of positive relation between the transaction costs threshold rankings and survival time rankings. For the evaluation of the relationship, we split the sectors into two groups; we then look to which extent sectors, which are ranked in the top group (top five) according to transaction cost thresholds, will be ranked in the top five according to survival rates. For the positive momentum effect the results are suggesting that 65% of rankings are placed correctly. This represents more than chance would suggest.

Results for the negative momentum effect are less even more pronounced, as 95% rankings are placed correctly. These results suggest that the model works well for both positive and negative momentum observations with the negative one being more pronounced. For this reason the survivorship model can be seen as a valid indicator for trading decisions and it implies that the longer sector survival time leads to higher break-even transaction costs.

V. Concluding remarks

This study investigates momentum effects in S&P Global 1200 Sector returns, based on survivorship analysis. These indices serve as an underlying of S&P Global Sector iShares, which replicate their performance and can be easily bought or sold at a comparatively low cost. An empirical KAPLAN-MEIER estimator is calculated for daily returns of ten S&P Global 1200 Sector Indices to estimate empirical survivor time of the daily momentum. For matters of comparison Monte-Carlo generated survivorship curves based on theoretical benchmark processes, specifically Random Walk and ARMA, are constructed.

Comparing mean survival times of empirical and synthetically generated curves allows us to identify sectors with longest survival rates. Sectors such as Technology, Utilities, Financials and Industrials show considerably longer positive momentum survival times than suggested by benchmark models, whereas Consumer Discretionary Sector shows strong negative survival rates. Further to this, results suggest that the Random Walk model underestimates empirical positive momentum survival times considerably, thus implying a violation of the market efficiency idea. The implementation of a trading rule based on this information proves to be successful in two ways. Firstly, the threshold levels for transaction costs show feasibility of the long only strategies for most indices, but the borrowing costs and large number of transactions contribute to the lesser feasibility of short only and particularly long/short strategies. Secondly, the results suggest a positive relation between the transaction cost thresholds ranking and survival time rankings. The ranking for positive momentum observations for all 10 sectors show that 65% of sectors, which are ranked in the top five according to transaction cost thresholds, are ranked in the top five according to survival rates. For negative momentum observations the results are even more pronounced, with 95% of correct placement. This implies that a longer mean survival rate leads to high transaction cost thresholds. Finally, the incorporation of dividends does not increase the feasibility of the trading strategies.

This study extends previous work in this area in two ways. First and foremost, the study employs a methodology which allows analyzing the momentum effect, without being heavily dependant on zero-arbitrage portfolios. This is interesting as the composites of these arbitrage portfolios are usually style-tilted and show different systematic risk profiles. Implying that the returns out of the portfolio are rewards for the systematic risk taken on. Secondly, the traditional concept of momentum analysis uses monthly data and constituency lists of indices or portfolios, whereas this study allows the analysis of daily data using only one time series.

The implementation of the trading rule can be improved by using parametric models, which allow the periodical estimation and prediction of momentum survival probabilities. In addition to the ideas above, it would be of interest to extend the model to different asset classes. Despite limitations the paper shows explicitly, that markets are not perfectly efficient and that an exploitable momentum effect, particularly the positive one, still exists.

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Table 1
Changes and Trend Construction (example)

Day	1	2	3	4	5	6	7	8	9
Price Change	**0.051**	**0.0004**	**-0.032**	**-0.043**	**0.046**	**0.023**	**0.01**	**-0.023**	**-0.014**
Pos.Trend	0	**1**	0	0	0	**1**	**1**	0	0
	Momentum dead	**Momentum alive**	Momentum dies away	Momentum dead	Momentum dead	**Momentum alive**	**Momentum alive**	Momentum dies away	Momentum dead
Neg. Trend	0	0	0	**1**	0	0	0	0	**1**
	Momentum dead	Momentum dead	Momentum dead	**Momentum alive**	Momentum dies away	Momentum dead	Momentum dead	Momentum dead	**Momentum alive**

Table 2: KAPLAN-MEIER Estimator: S&P Global 1200 Consumer Discretionary

Survival Function of positive Market Momentum

	Ordered failure time	intact before t	ending at time t	contribution to KM estimator	KM estimator	Variance	Hazard Rate
j	t(j)	nj	dj	(1-(dj/nj))	S(t)	VAR(S(t))	LAMDA(t)
1	2	650	282	56.6154%	**56.6154%**	0.000378	43.3846%
2	3	368	171	53.5326%	**30.3077%**	0.000217	46.4674%
3	4	197	93	52.7919%	**16.0000%**	0.000116	47.2081%
4	5	104	53	49.0385%	**7.8462%**	0.000062	50.9615%
5	6	51	25	50.9804%	**4.0000%**	0.000030	49.0196%
6	7	26	15	42.3077%	**1.6923%**	0.000015	57.6923%
7	8	11	5	54.5455%	**0.9231%**	0.000006	45.4545%
8	9	6	4	33.3333%	**0.3077%**	0.000003	66.6667%
9	10	2	1	50.0000%	**0.1538%**	0.000001	50.0000%
10	11	1	1	0.0000%	**0.0000%**	0.000000	0.0000%

Survival Function of negative Market Momentum

	Ordered failure time	intact before t	ending at time t	contribution to KM estimator	KM estimator	Variance	Hazard Rate
j	t(j)	nj	dj	(1-(dj/nj))	S(t)	VAR(S(t))	LAMDA(t)
1	2	585	257	56.0684%	**56.0684%**	0.000421	43.9316%
2	3	328	146	55.4878%	**31.1111%**	0.000237	44.5122%
3	4	182	83	54.3956%	**16.9231%**	0.000132	45.6044%
4	5	99	42	57.5758%	**9.7436%**	0.000071	42.4242%
5	6	57	21	63.1579%	**6.1538%**	0.000039	36.8421%
6	7	36	13	63.8889%	**3.9316%**	0.000024	36.1111%
7	8	23	9	60.8696%	**2.3932%**	0.000016	39.1304%
8	9	14	6	57.1429%	**1.3675%**	0.000010	42.8571%
9	10	8	4	50.0000%	**0.6838%**	0.000006	50.0000%
10	11	4	2	50.0000%	**0.3419%**	0.000003	50.0000%
11	12	2	1	50.0000%	**0.1709%**	0.000001	50.0000%
12	13	1	1	0.0000%	**0.0000%**	0.000000	0.0000%

Table 3
Random Walk and ARMA Simulation of
KAPLAN-MEIER Estimator for S&P Global 1200 Consumer Discretionary

Trend
Simulation

Monte Carlo 1: Random Walk

POSITIVE				NEGATIVE			
t(j)	Mean	Stdv	T-stat	**t(j)**	Mean	Stdv	T-stat
2	**49.930%**	0.0213	23.3933	**2**	**49.896%**	0.0213	23.4778
3	**25.415%**	0.0154	16.4852	**3**	**22.771%**	0.0138	16.5427
4	**13.373%**	0.0116	11.4853	**4**	**9.922%**	0.0086	11.5693
5	**6.468%**	0.0081	7.9942	**5**	**4.560%**	0.0056	8.0784
6	**2.794%**	0.0051	5.4466	**6**	**1.797%**	0.0033	5.4352
7	**1.093%**	0.0032	3.4567	**7**	**0.693%**	0.0020	3.4564
8	**0.379%**	0.0019	2.0358	**8**	**0.158%**	0.0008	2.0558
9	**0.061%**	0.0005	1.2259	**9**	**0.000%**	0.0000	0.0000

Monte Carlo 2: ARMA Process

POSITIVE				NEGATIVE			
t(j)	Mean	Stdv	T-stat	**t(j)**	Mean	Stdv	T-stat
2	**54.195%**	0.0204	26.5104	**2**	**54.227%**	0.0205	26.5153
3	**30.157%**	0.0154	19.6283	**3**	**29.444%**	0.0151	19.5592
4	**16.168%**	0.0113	14.2788	**4**	**16.218%**	0.0113	14.3234
5	**9.488%**	0.0091	10.4602	**5**	**9.824%**	0.0094	10.4360
6	**5.722%**	0.0077	7.4071	**6**	**5.330%**	0.0071	7.4718
7	**2.990%**	0.0059	5.1040	**7**	**2.663%**	0.0052	5.1608
8	**1.602%**	0.0048	3.3495	**8**	**1.038%**	0.0031	3.3686
9	**0.844%**	0.0041	2.0625	**9**	**0.291%**	0.0014	2.0878
10	**0.315%**	0.0024	1.3150	**10**	**0.060%**	0.0004	1.3399
11	**0.137%**	0.0015	0.8859				
12	**0.060%**	0.0010	0.6276				
13	**0.018%**	0.0004	0.4428				

Table 4
Mean values for sector survival times

	POSITIVE MOMENTUM		
SECTORS	Mean empirical survival time	Mean RW survival time	Mean ARMA survival time
S&P GLOBAL 1200 CONS DISCRETNRY	2.178461538	1.994512392	2.21165424
S&P GLOBAL 1200 CONS STAPLES	2.04957265	1.978012367	2.135102741
S&P GLOBAL 1200 ENERGY	1.98757764	1.929939488	2.05607048
S&P GLOBAL 1200 FINANCIALS	2.233281493	2.015370869	2.09242621
S&P GLOBAL 1200 HEALTH CARE	2.031719533	2.006649916	2.219997878
S&P GLOBAL 1200 INDUSTRIALS	2.244131455	2.028471715	2.030593368
S&P GLOBAL 1200 MATERIALS	2.382395382	1.970905746	2.304161817
S&P GLOBAL 1200 TELECOM. SVS.	2.025553663	1.993781635	2.081041225
S&P GLOBAL 1200 UTILITIES	2.217532468	2.090520246	2.11659203
S&P GLOBAL 1200 INFO. TECH	2.386749	2.016823	2.156299
	NEGATIVE MOMENTUM		
SECTORS	Mean empirical survival time	Mean RW survival time	Mean ARMA survival time
S&P GLOBAL 1200 CONS DISCRETNRY	2.288888889	1.8979657	2.190351434
S&P GLOBAL 1200 CONS STAPLES	1.903811252	1.939850545	2.106823259
S&P GLOBAL 1200 ENERGY	1.855805243	1.986521463	2.135618466
S&P GLOBAL 1200 FINANCIALS	2.104424779	1.94355337	2.212234306
S&P GLOBAL 1200 HEALTH CARE	1.869485294	2.064898415	2.237841516
S&P GLOBAL 1200 INDUSTRIALS	1.97338403	1.955025826	2.15898729
S&P GLOBAL 1200 MATERIALS	2.339160839	1.953534514	2.360920159
S&P GLOBAL 1200 TELECOM. SVS.	2.061749571	1.975899492	2.092345215
S&P GLOBAL 1200 UTILITIES	1.872798434	2.02608715	2.065218867
S&P GLOBAL 1200 INFO. TECH	2.014787	2.024806	2.098623

Table 5

Borrowing rates for S&P 1200 Global Sector iShares:

iShares S&P Global Consumer Discretionary Sector Index Fund	2.25%
iShares S&P Global Consumers Staples Sector Index Fund	2.50%
iShares S&P Global Energy Sector Index Fund	2.50%
iShares S&P Global Financials Sector Index Fund	2.00%
iShares S&P Global Healthcare Sector Index Fund.	1.75%
iShares S&P Global Industrials Sector Index Fund	2.50%
iShares S&P Global Materials Sector Index Fund	3.75%
iShares S&P Global Telecommunications Sector Index Fund	4.25%
iShares S&P Global Utilities Sector Index Fund	3.00%
iShares S&P Global Technology Sector Index Fund	3.00%

Table 6
Annualized holding period returns, Standard Deviations and Sharpe Ratios

		Price Index				Total Return Index			
		BUY & HOLD	LONG	SHORT	LONG/SHORT	BUY & HOLD	LONG	SHORT	LONG/SHORT
S&P GLOBAL 1200 CONS DISCRETNRY	Annualised Return	4.10%	15.48%	11.00%	23.46%	4.95%	15.92%	10.60%	23.50%
	Standard Deviation	16.79%	16.68%	18.50%	24.89%	16.79%	16.68%	18.50%	24.89%
	Sharpe Ratio	0.064	0.747	0.431	0.821	0.115	0.773	0.410	0.823
S&P GLOBAL 1200 CONS STAPLES	Annualised Return	3.42%	7.98%	2.78%	7.74%	4.27%	8.41%	2.37%	7.76%
	Standard Deviation	12.26%	12.13%	13.48%	18.13%	12.26%	12.13%	13.48%	18.13%
	Sharpe Ratio	0.033	0.409	-0.018	0.260	0.102	0.444	-0.048	0.261
S&P GLOBAL 1200 FINANCIALS	Annualised Return	4.85%	17.05%	5.18%	19.22%	5.70%	17.49%	4.79%	19.26%
	Standard Deviation	17.74%	18.14%	19.34%	26.50%	17.74%	18.14%	19.34%	26.51%
	Sharpe Ratio	0.103	0.773	0.112	0.611	0.151	0.798	0.091	0.612
S&P GLOBAL 1200 HEALTH CARE	Annualised Return	3.33%	9.33%	-3.20%	3.11%	4.18%	9.77%	-3.60%	3.14%
	Standard Deviation	16.39%	16.83%	18.00%	24.65%	16.39%	16.83%	18.00%	24.65%
	Sharpe Ratio	0.019	0.375	-0.345	0.004	0.071	0.401	-0.368	0.005
S&P GLOBAL 1200 INDUSTRIALS	Annualised Return	3.97%	13.93%	-2.86%	8.04%	4.82%	14.38%	-3.26%	8.09%
	Standard Deviation	16.23%	16.41%	17.33%	23.88%	16.23%	16.41%	17.33%	23.88%
	Sharpe Ratio	0.058	0.665	-0.340	0.210	0.111	0.692	-0.363	0.212
S&P GLOBAL 1200 MATERIALS	Annualised Return	7.39%	15.87%	17.49%	30.35%	8.24%	16.32%	17.11%	30.41%
	Standard Deviation	16.38%	16.77%	18.32%	24.80%	16.38%	16.78%	18.32%	24.80%
	Sharpe Ratio	0.266	0.766	0.790	1.102	0.318	0.793	0.769	1.104
S&P GLOBAL 1200 ENERGY	Annualised Return	7.62%	26.15%	-11.00%	12.12%	8.47%	26.60%	-11.40%	12.17%
	Standard Deviation	19.73%	21.37%	21.28%	30.20%	19.73%	21.37%	21.28%	30.20%
	Sharpe Ratio	0.233	1.082	-0.659	0.301	0.276	1.103	-0.678	0.303
S&P GLOBAL 1200 TELECOM. SERVICES	Annualised Return	-0.52%	8.64%	5.09%	10.71%	0.32%	9.06%	4.68%	10.72%
	Standard Deviation	19.16%	20.13%	20.43%	28.67%	19.16%	20.13%	20.43%	28.67%
	Sharpe Ratio	-0.185	0.279	0.101	0.268	-0.141	0.300	0.081	0.268
S&P GLOBAL 1200 UTILITIES	Annualised Return	4.64%	10.39%	4.18%	11.55%	5.49%	10.84%	3.79%	11.60%
	Standard Deviation	12.30%	12.24%	13.25%	18.03%	12.30%	12.24%	13.25%	18.03%
	Sharpe Ratio	0.132	0.602	0.087	0.473	0.201	0.639	0.058	0.476
S&P GLOBAL 1200 INFO. TECH.	Annualised Return	0.09%	16.91%	9.40%	23.30%	0.93%	17.36%	9.01%	23.35%
	Standard Deviation	29.08%	27.06%	32.57%	42.33%	29.08%	27.06%	32.57%	42.33%
	Sharpe Ratio	-0.101	0.513	0.196	0.479	-0.072	0.530	0.184	0.480

Table 7

End of Period Values, initial investment $100

PANEL A	End of Period Values of $100 initial investment: No Transaction Costs (in $)			
PRICE INDEX	Buy & Hold Index	Long Momentum	Short Momentum	Long/Short
S&P GLOBAL 1200 CONS DISCRETNRY	146.111	417.835	285.577	902.331
S&P GLOBAL 1200 CONS STAPLES	137.201	209.003	132.201	208.942
S&P GLOBAL 1200 FINANCIALS	156.606	483.281	175.809	642.506
S&P GLOBAL 1200 HEALTH CARE	136.045	236.895	78.692	140.969
S&P GLOBAL 1200 INDUSTRIALS	144.297	362.226	78.422	214.809
S&P GLOBAL 1200 MATERIALS	197.899	433.190	506.645	1659.659
S&P GLOBAL 1200 ENERGY	202.151	1119.658	36.987	313.163
S&P GLOBAL 1200 TELECOM. SVS.	95.294	222.103	152.337	255.857
S&P GLOBAL 1200 UTILITIES	153.538	261.216	147.119	290.607
S&P GLOBAL 1200 INFO. TECH.	100.815	477.121	238.306	859.806
PANEL B	**End of Period Values of $100 initial investment: No Transaction Costs (in $)**			
TOTAL RETURNS INDEX	**Buy & Hold Index**	**Long Momentum**	**Short Momentum**	**Long/Short**
S&P GLOBAL 1200 CONS DISCRETNRY	171.475	453.477	264.666	907.592
S&P GLOBAL 1200 CONS STAPLES	170.582	233.332	119.033	210.028
S&P GLOBAL 1200 FINANCIALS	210.147	562.055	146.804	623.956
S&P GLOBAL 1200 HEALTH CARE	162.058	258.943	72.365	141.700
S&P GLOBAL 1200 INDUSTRIALS	170.296	394.842	72.584	216.720
S&P GLOBAL 1200 MATERIALS	237.716	477.081	448.016	1616.306
S&P GLOBAL 1200 ENERGY	246.695	1241.515	33.691	316.301
S&P GLOBAL 1200 TELECOM. SVS.	131.626	260.848	129.168	254.788
S&P GLOBAL 1200 UTILITIES	205.073	303.957	128.673	295.758
S&P GLOBAL 1200 INFO. TECH.	109.015	497.067	229.830	863.892

Table 8

Trading Rule Results based on Price and Total Return indices:

PANEL A	END VALUE OPTIMISATION			CV OPTIMISATION			SR OPTIMISATION		
Price Index	LONG (BPS)	SHORT (BPS)	LONG/SHORT (BPS)	LONG (BPS)	SHORT (BPS)	LONG/SHORT (BPS)	LONG (BPS)	SHORT (BPS)	LONG/SHORT (BPS)
S&P GLOBAL 1200 CONS DISCRETNRY	**13.12**	**17.46**	11.61	**13.12**	**16.38**	10.41	**13.12**	**17.17**	11.29
S&P GLOBAL 1200 CONS STAPLES	4.96	-0.88	2.48	4.98	-1.61	1.58	4.96	-0.96	2.38
S&P GLOBAL 1200 FINANCIALS	**13.70**	2.87	8.67	**13.52**	1.83	7.28	**13.64**	2.48	8.15
S&P GLOBAL 1200 HEALTH CARE	6.43	-13.13	0.21	6.32	-13.81	-0.70	6.42	-13.19	0.12
S&P GLOBAL 1200 INDUSTRIALS	11.10	-14.90	2.41	11.01	-15.45	1.36	11.08	-15.03	2.16
S&P GLOBAL 1200 MATERIALS	9.84	**25.45**	**13.86**	9.57	**23.00**	11.49	9.67	**23.99**	**12.45**
S&P GLOBAL 1200 ENERGY	**20.15**	-41.08	2.61	**19.36**	-42.17	0.39	**19.67**	-41.75	1.26
S&P GLOBAL 1200 TELECOM. SVS.	10.18	11.47	5.99	10.21	11.59	6.14	10.40	**12.04**	6.99
S&P GLOBAL 1200 UTILITIES	6.23	-1.03	3.79	6.23	-1.82	2.59	6.23	-1.31	3.37
S&P GLOBAL 1200 INFO. TECH.	**19.01**	**21.68**	**13.30**	**19.01**	**21.68**	**13.30**	**18.82**	**22.54**	**14.08**
PANEL B	**END VALUE OPTIMISATION**			**CV OPTIMISATION**			**SR OPTIMISATION**		
Total Returns Index	LONG (BPS)	SHORT (BPS)	LONG/SHORT (BPS)	LONG (BPS)	SHORT (BPS)	LONG/SHORT (BPS)	LONG (BPS)	SHORT (BPS)	LONG/SHORT (BPS)
S&P GLOBAL 1200 CONS DISCRETNRY	**12.15**	11.31	10.62	**12.15**	9.81	8.93	**12.15**	10.58	9.80
S&P GLOBAL 1200 CONS STAPLES	3.69	-8.51	1.23	3.73	-9.71	-0.28	3.71	-9.08	0.51
S&P GLOBAL 1200 FINANCIALS	11.97	-8.91	6.69	11.67	-10.51	4.41	11.79	-9.90	5.26
S&P GLOBAL 1200 HEALTH CARE	5.43	-19.33	-0.79	5.26	-20.40	-2.22	5.36	-19.78	-1.39
S&P GLOBAL 1200 INDUSTRIALS	10.14	-20.84	1.46	10.01	-21.61	-0.06	10.08	-21.21	0.74
S&P GLOBAL 1200 MATERIALS	8.75	**17.16**	**12.49**	8.41	**14.21**	9.51	8.52	**15.16**	10.46
S&P GLOBAL 1200 ENERGY	**19.03**	-48.16	1.48	**18.01**	-49.54	-1.37	**18.33**	-49.10	-0.49
S&P GLOBAL 1200 TELECOM. SVS.	8.23	-0.46	4.01	8.04	-0.90	3.17	8.23	-0.45	4.02
S&P GLOBAL 1200 UTILITIES	4.61	-11.24	2.18	4.61	-12.48	0.18	4.61	-12.00	0.95
S&P GLOBAL 1200 INFO. TECH.	**18.55**	**18.79**	**12.85**	**18.61**	**18.52**	**12.60**	**18.43**	**19.40**	**13.40**

Table 9
Sector Ranking Scheme

SECTORS	LONG (POSITIVE MOMENTUM)				
	Absolute Ranking		Relative ranking		
	Transaction Costs level	Empirical survival Time (EMP)	Difference EMP/RW	Difference EMP/ARMA	Difference EMP/comb.
S&P GLOBAL 1200 CONS DISCRETNRY	**4**	6	5	6	6
S&P GLOBAL 1200 CONS STAPLES	10	7	7	9	8
S&P GLOBAL 1200 ENERGY	**1**	10	8	8	7
S&P GLOBAL 1200 FINANCIALS	**3**	4	3	3	4
S&P GLOBAL 1200 HEALTH CARE	8	8	10	10	10
S&P GLOBAL 1200 INDUSTRIALS	5	3	4	2	3
S&P GLOBAL 1200 MATERIALS	7	2	1	5	2
S&P GLOBAL 1200 TELECOM. SVS.	6	9	9	7	9
S&P GLOBAL 1200 UTILITIES	9	5	6	4	5
S&P GLOBAL 1200 INFO. TECH	**2**	1	2	1	1

SECTORS	SHORT (NEGATIVE MOMENTUM)				
	Absolute Ranking		Relative ranking		
	Transaction Costs level	Empirical survival Time (EMP)	Difference EMP/RW	Difference EMP/ARMA	Difference EMP/comb.
S&P GLOBAL 1200 CONS DISCRETNRY	**3**	2	1	1	1
S&P GLOBAL 1200 CONS STAPLES	6	7	7	8	7
S&P GLOBAL 1200 ENERGY	10	10	8	9	9
S&P GLOBAL 1200 FINANCIALS	**5**	3	3	5	4
S&P GLOBAL 1200 HEALTH CARE	8	9	10	10	10
S&P GLOBAL 1200 INDUSTRIALS	9	6	5	6	6
S&P GLOBAL 1200 MATERIALS	**1**	1	2	2	2
S&P GLOBAL 1200 TELECOM. SVS.	**4**	4	4	3	3
S&P GLOBAL 1200 UTILITIES	7	8	9	7	8
S&P GLOBAL 1200 INFO. TECH	**2**	5	6	4	5

APPENDIX: Table 10

Kaplan-Meier Estimator, Random Walk and ARMA Simulation of Kaplan-Meier Estimator for S&P Global 1200 Sectors:

The columns describe the (simulated) probability that a trend will continue beyond time t=t(j). *, **,*** indicate significance levels of 10%, 5% and 1%.

S&P GLOBAL 1200 CONSUMER STAPLES						
	Positive Momentum			**Negative Momentum**		
Ordered failure time	KM estimator	Random Walk	ARMA Process	KM estimator	Random Walk	ARMA Process
t(j)	S(t)	Mean	Mean	S(t)	Mean	Mean
2	53.16%	49.91%***	52.97%***	49.36%	49.90%***	52.97%***
3	27.18%	25.60%***	27.80%***	23.59%	24.20%***	28.29%***
4	13.68%	12.74%***	14.96%***	10.53%	11.74%***	15.56%***
5	6.50%	5.42%***	8.34%***	4.54%	5.36%***	7.78%***
6	3.08%	2.31%***	4.75%***	1.27%	2.00%***	3.46%***
7	1.03%	1.20%***	2.54%***	0.54%	0.61%***	1.61%***
8	0.34%	0.62%***	1.41%***	0.36%	0.16%***	0.73%***
9	0.00%	0.25%	0.73%*	0.18%	0.06%	0.28%*
10		0.08%	0.28%			
11		0.02%	0.08%			
12			0.02%			
S&P GLOBAL 1200 ENERGY						
	Positive Momentum			**Negative Momentum**		
Ordered failure time	KM estimator	Random Walk	ARMA Process	KM estimator	Random Walk	ARMA Process
t(j)	S(t)	Mean	Mean	S(t)	Mean	Mean
2	52.80%	49.89%***	53.13%***	47.75%	49.93%***	53.09%***
3	25.47%	23.82%***	26.97%***	22.85%	24.35%***	28.69%***
4	11.96%	11.04%***	13.33%***	9.55%	12.39%***	15.36%***
5	5.59%	4.67%***	6.60%***	3.93%	5.93%***	8.11%***
6	2.17%	2.26%***	3.04%***	1.31%	3.21%***	4.14%***
7	0.78%	0.99%***	1.40%***	0.19%	1.88%***	2.10%***
8	0.00%	0.33%***	0.75%***	0.00%	0.96%***	1.23%***
9		0.13%	0.37%*		0.41%	0.82%*
10			0.12%		0.16%	0.54%
11			0.04%		0.07%	0.29%
12					0.03%	0.14%
13					0.01%	0.05%
14						0.02%
15						0.01%
S&P GLOBAL 1200 FINANCIALS						
	Positive Momentum			**Negative Momentum**		
Ordered failure time	KM estimator	Random Walk	ARMA Process	KM estimator	Random Walk	ARMA Process
t(j)	S(t)	Mean	Mean	S(t)	Mean	Mean
2	55.21%	49.93%***	55.08%***	50.27%	49.90%***	55.11%***
3	30.48%	24.98%***	28.70%***	25.49%	24.04%***	31.58%***
4	17.26%	12.58%***	13.88%***	14.16%	11.79%***	17.11%***
5	9.33%	6.89%***	6.24%***	8.50%	5.30%***	9.03%***
6	5.44%	3.93%***	3.05%***	5.13%	1.98%***	4.61%***
7	2.95%	1.97%***	1.50%***	3.19%	0.87%***	2.23%***
8	1.56%	1.25%***	0.64%***	1.95%	0.48%***	0.96%***
9	0.78%	0.69%	0.17%***	1.06%	0.19%	0.59%***

10	0.31%	0.34%	0.07%	0.53%	0.04%	0.37%
11		0.15%				0.18%
12		0.06%				0.09%
13		0.01%				0.04%
14						0.01%
S&P GLOBAL 1200 HEALTH CARE						
	Positive Momentum			**Negative Momentum**		
Ordered failure time	KM estimator	Random Walk	ARMA Process	KM estimator	Random Walk	ARMA Process
t(j)	S(t)	Mean	Mean	S(t)	Mean	Mean
2	50.25%	49.95%***	53.77%***	48.90%	49.94%***	53.76%***
3	24.37%	25.07%***	30.62%***	22.61%	26.75%***	30.37%***
4	12.52%	13.05%***	16.61%***	9.01%	14.05%***	17.74%***
5	6.51%	6.70%***	9.66%***	4.23%	7.70%***	10.41%***
6	3.17%	3.34%***	5.38%***	1.65%	4.25%***	5.75%***
7	1.67%	1.75%***	3.29%***	0.55%	2.46%***	3.31%***
8	1.17%	0.80%***	1.81%***		1.34%***	1.66%***
9	1.00%	0.26%	0.85%		0.76%**	0.78%**
10	0.83%	0.04%	0.40%		0.35%	0.34%
11	0.67%		0.12%		0.14%	0.12%
12	0.50%		0.02%		0.05%	0.05%
13	0.33%				0.02%	0.02%
14	0.17%				0.01%	
15					0.00%	
S&P GLOBAL 1200 INDUSTRIALS						
	Positive Momentum			**Negative Momentum**		
Ordered failure time	KM estimator	Random Walk	ARMA Process	KM estimator	Random Walk	ARMA Process
t(j)	S(t)	Mean	Mean	S(t)	Mean	Mean
2	56.03%	49.91%***	53.27%***	49.05%	49.88%***	53.25%***
3	31.92%	25.95%***	26.44%***	24.71%	24.63%***	28.98%***
4	17.53%	13.36%***	12.83%***	11.60%	11.72%***	15.56%***
5	9.39%	7.14%***	6.14%***	6.08%	5.40%***	8.08%***
6	5.32%	3.81%***	2.89%***	3.42%	2.52%***	4.54%***
7	2.97%	1.79%***	1.13%***	1.71%	1.04%***	2.64%***
8	1.10%	0.89%***	0.27%***	0.57%	0.32%***	1.73%***
9	0.16%	0.35%	0.08%*	0.19%		1.12%*
10		0.12%				0.55%
11		0.05%				0.26%
12		0.01%				0.09%
13						0.03%
S&P GLOBAL 1200 MATERIALS						
	Positive Momentum			**Negative Momentum**		
Ordered failure time	KM estimator	Random Walk	ARMA Process	KM estimator	Random Walk	ARMA Process
t(j)	S(t)	Mean	Mean	S(t)	Mean	Mean
2	58.87%	49.90%***	56.78%***	57.34%	49.89%***	56.76%***
3	32.90%	24.82%***	31.80%***	31.99%	25.67%***	33.87%***
4	18.90%	12.42%***	18.57%***	17.83%	11.69%***	19.68%***
5	11.69%	5.42%***	10.84%***	9.62%	4.96%***	11.70%***
6	7.36%	2.44%***	6.42%***	5.24%	1.99%***	6.67%***
7	4.33%	1.40%***	3.39%***	3.32%	0.80%***	3.88%***
8	2.31%	0.71%***	1.65%***	2.45%	0.36%***	2.01%***
9	1.15%	0.31%	0.74%***	1.92%	0.11%	1.06%***
10	0.58%	0.17%	0.22%*	1.40%		0.47%*
11	0.14%	0.08%	0.06%	1.05%		0.26%
12		0.03%		0.70%		0.15%

13		0.01%		0.52%		0.07%
14				0.35%		0.03%
15				0.17%		0.01%
S&P GLOBAL 1200 TELECOMMUNICATION SERVICES						
	Positive Momentum			**Negative Momentum**		
Ordered failure time	KM estimator	Random Walk	ARMA Process	KM estimator	Random Walk	ARMA Process
t(j)	S(t)	Mean	Mean	S(t)	Mean	Mean
2	51.79%	49.88%***	54.36%***	52.66%	49.91%***	54.35%***
3	24.87%	24.62%***	27.64%***	26.93%	24.86%***	28.15%***
4	12.44%	12.77%***	13.61%***	14.41%	12.44%***	14.77%***
5	6.64%	6.99%***	6.73%***	6.86%	5.99%***	6.90%***
6	3.75%	3.21%***	3.14%***	2.40%	2.73%***	3.16%***
7	1.70%	1.42%***	1.50%***	1.20%	1.27%***	1.24%***
8	0.85%	0.48%***	0.72%***	0.69%	0.38%***	0.51%***
9	0.34%	0.19%	0.41%***	0.51%	0.12%	0.15%***
10	0.17%	0.09%	0.20%	0.34%	0.04%	
11		0.03%	0.09%	0.17%		
12			0.03%			
S&P GLOBAL 1200 UTILITIES						
	Positive Momentum			**Negative Momentum**		
Ordered failure time	KM estimator	Random Walk	ARMA Process	KM estimator	Random Walk	ARMA Process
t(j)	S(t)	Mean	Mean	S(t)	Mean	Mean
2	54.22%	49.93%***	52.47%***	47.75%	49.92%***	52.49%***
3	30.19%	27.13%***	28.12%***	22.70%	26.29%***	27.66%***
4	17.05%	15.07%***	14.98%***	10.57%	13.90%***	13.91%***
5	8.77%	8.19%***	8.15%***	4.70%	6.61%***	6.69%***
6	4.22%	4.69%***	4.49%***	1.57%	3.25%***	3.27%***
7	2.11%	2.65%***	2.06%***		1.68%***	1.64%***
8	1.62%	1.39%***	0.93%***		0.95%***	0.65%***
9	1.14%	0.55%	0.45%*		0.53%	0.21%*
10	0.81%	0.17%	0.17%		0.28%	0.05%
11	0.65%	0.05%	0.04%		0.15%	
12	0.49%				0.07%	
13	0.32%				0.03%	
14	0.16%				0.01%	
S&P GLOBAL 1200 INFORMATION TECHNOLOGY						
	Positive Momentum			**Negative Momentum**		
Ordered failure time	KM estimator	Random Walk	ARMA Process	KM estimator	Random Walk	ARMA Process
t(j)	S(t)	Mean	Mean	S(t)	Mean	Mean
2	57.63%	49.88%***	52.73%***	52.50%	49.88%***	52.71%***
3	33.44%	24.72%***	29.53%***	26.80%	25.00%***	27.64%***
4	19.11%	12.86%***	15.87%***	12.75%	12.84%***	15.40%***
5	11.71%	6.89%***	8.61%***	5.73%	6.87%***	7.52%***
6	7.09%	3.79%***	4.30%***	2.40%	4.01%***	3.63%***
7	4.01%	2.26%***	2.37%***	1.11%	2.41%***	1.69%***
8	2.47%	1.27%***	1.49%***	0.18%	1.46%***	0.80%***
9	1.54%	0.63%	0.73%*		0.69%	0.49%*
10	0.77%	0.26%	0.28%		0.27%	0.26%
11	0.46%	0.08%	0.07%		0.07%	0.14%
12	0.31%	0.01%	0.02%			0.06%
13	0.15%					0.02%
14						0.01%