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A Guide to Survival of Momentum in UK Style Portfolios

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In this study we estimate the survival time of momentum in six UK style portfolios returns in the period October 1980 – June 2014. We utilise the Kaplan-Meier estimator, a non-parametric method that measures the probability that momentum will persist beyond the present month. This probability enables us to compute the average momentum survival time for each of the six style portfolios. Discrepancies between these empirical mean survival times to those implied by theoretical models (Random Walk and ARMA (1, 1)) show that there is scope for profiting from momentum trading. We illustrate this by forming long-only, short-only and long-short trading strategies that exploit positive and negative momentum and their average survival time. Our trading strategies show that utilising momentum mean survival time yields considerably higher Sharpe ratios than the naïve buy-and-hold at a feasible level of transaction costs. This finding is most pronounced among the long/short strategies.

JEL classification: G14, G11

Key words: Momentum survival, Style portfolios, Kaplan-Meier estimator, Trading strategies

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1   Introduction

This study contributes to the equity momentum literature by examining and exploiting the survival time of momentum in the UK style portfolio returns. The seminal paper of Jegadeesh and Titman (1993) was the first to document the outperformance of momentum trading strategies. While a significant body of research finds that trading strategies based on predictive firm characteristics (such as size, book to market ratio, leverage etc.) weaken in performance over time[1], robustness of momentum investment strategy is confirmed in a number of US studies, such as Chan, Jegadeesh, & Lakonishok (1996), Jegadeesh and Titman (2001, 2002) and Asness, Moskowitz and Pedersen (2013). Momentum profits are not restricted to the US market only; a point verified by Hon and Tonks (2003), Chelley-Steeley & Siganos (2004), Gregory, Tharyan, & Christidis (2013) and Liu, Strong, & Xu (1999) who all find evidence of momentum effect in UK stock market, while Rouwenhorst (1998) documents momentum for 12 European countries.

One stream of momentum literature focuses on investigating the presence of momentum in the US style (value, growth, small cap) portfolios (see for instance Lewellen , 2002; Chen , 2003; Chen and De Bondt, 2004; Froot and Teo, 2004 and Chen, Jiang and Zhu, 2012). Similarly, Clare, Sapuric and Todorovic (2010) find that exploiting momentum in UK style portfolios proves to be a profitable investment strategy for investors following style rotation strategy. More recently, Avramov, Cheng, Schreiber and Shemer (2016) investigate momentum among 15 market anomalies in the US (total accruals, net operating assets, momentum, gross profitability, book-to-market among others). They document that while the profitability of momentum in individual anomalies fades over time, a long-short trading strategy based on a combination of winner (best performing, long position) and loser (worst performing, short position) anomalies according to lagged one-month returns generate significantly positive risk-adjusted returns and outperform naïve benchmark. Further, they show that momentum profits are time varying and are stronger following high investor sentiment periods, similar to Stambaugh, Yu and Yuan (2012).

Previous literature is in agreement that 1) momentum is present across various markets and across style portfolios and that 2) momentum profits diminish over time. However, there is a clear gap in the literature as to how long do momentum returns persist, particularly in style portfolios, i.e. portfolios where stocks are selected based on firm characteristics that resemble

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[1]See for instance recent work by Chordia, Roll and Subrahmanyam(2011) and McLean and Pontiff (2016)

a particular 'investment style'. In this study, we contribute to the literature by measuring the longevity (survival time) of momentum on the UK equivalents of six Fama-French size/style portfolios based on popular market anomalies: size and book-to-market ratio (BTM hereafter). To investigate the survival of the momentum we follow Jochum (2000) and Kos and Todorovic (2008) approach by constructing survival curves[2]. The study of Jochum (2000) is somewhat basic in the sense that it only identifies whether the empirical and theoretical survival curves are identical or not to explore whether the market momentum (empirical) survives longer than it should (theoretical). Kos and Todorovic (2008) extend the study of Jochum (2000) and derive trading strategies to exploit the misaligned theoretical and empirical momentum survival of US sector returns. However, neither of the two studies tests the empirical survival times in equity style portfolios, whether the empirical momentum survivals vary across business cycles or weather the estimation of momentum survival times leads to profitable momentum trading during the turbulent market conditions such as the financial crises. Our study addresses these questions and performs analysis across economic regimes and in the recent financial crisis period separately. Hence, our study fills several gaps in the literature and extends the application of survival methodology in the investment management, in particular in the style timing literature.

Specifically, we apply the Kaplan–Meier estimator (Kaplan and Meier, 1958; KM hereafter), a non-parametric method that in our setting measures the likelihood that a positive/negative momentum will persist beyond the present day. In addition to estimating survival time, this model enables us to identify profit potential and feasibility of momentum trading in style portfolios. Kos and Todorovic (2008) emphasise that the KM survival methodology has a clear advantage over the Jegadeesh and Titman (1993) approach as it does not depend on zero-cost, no arbitrage portfolios which only hypothetically have zero betas and leave investors exposed to systematic risk. Further, momentum studies based on the Jegadeesh and Titman (1993) approach apply various holding periods to momentum portfolios (1, 3, 6, 8, 12 months being most common) to establish the persistence of momentum strategy profitability. The KM survival analysis method estimates the persistence (survival time) of the momentum in a portfolio return, without the need to test for various holding periods. In this study we apply the KM methodology for in-sample estimation of momentum mean survival times in a number of UK style portfolios. We then provide out-of-sample tests on profitability of momentum strategies based on holding periods suggested by survival analysis.

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[2]Kiefer(1988) provides a survey of economic survival and hazard functions

Hence, to the best of our knowledge, this study is the first to address survival time of the momentum in the style portfolio returns. The study includes the period of recent financial crises that prior studies based on KM estimator do not cover. Specifically, we use monthly data in the period October 1980 to June 2014 for six UK style portfolios: Small Size & Low BTM (SL), Small Size & Medium BTM (SM), Small Size & High BTM (SH), Big Size & Low BTM (BL), Big Size & Medium BTM (BM) and Big Size & High BTM (BH)[3]. We construct empirical survival curves for momentum in each portfolio and calculate average momentum survival time (in months). We compare the empirical mean of momentum survival with the one obtained with simulated theoretical benchmarks. To establish theoretical (benchmark) momentum survival times, we deploy Monte-Carlo simulation of two commonly cited models in the description of stock returns: the Random Walk and ARMA (1,1) model.

Any departure of empirical survival time obtained with KM estimator from the theoretical one presents an arbitrage opportunity. We exploit this opportunity for each style portfolio separately and for a combination of style portfolios. For each style portfolio, we apply long-only trading rule that buys that style portfolio once a positive momentum signal is triggered and holds it for average survival time of the positive momentum. Similarly the short-only trading rule calls for selling/short-selling of a style portfolio upon initiation of a negative momentum signal and holding that portfolio for the average negative momentum survival time. In addition, we combine the long-only and short-only rule for *each* style portfolio separately into a long-short trading rule. Finally, we form a long-short 'winner-loser' rule that implies switching *across* style portfolios so that: in month t we buy the winner style portfolio (highest positive momentum) and hold it for the average positive momentum survival time, and short-sell the loser style portfolio (lowest negative momentum) and hold the position over average negative momentum survival time. The winner/loser strategy implies that investor is engaged in exploiting momentum through style-rotation, an approach proven profitable in the UK in Clare, Sapuric and Todorovic (2010) and Levis and Liodakis (1999).

We gauge profitability of strategies by comparing their Sharpe ratio to the buy-and-hold of the corresponding style portfolio. We estimate the feasibility of our trading rule by calculating breakeven transaction costs, which represent maximum costs that investor can pay and still equalise the Sharpe ratio of the trading strategy to that of the buy and hold.

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[3] As defined in Gregory, Tharyan and Christidis (2013)

Additionally, given that strength of momentum profits varies over time (Stambaugh et al., 2012; and Avramov et al., 2016) and that UK momentum premium exhibits cyclical behaviour (Sarwar, Mateus and Todorovic, 2016), we evaluate if there are any differences in the probabilities of momentum trading across UK business cycles.

Our findings reveal that positive momentum lasts longer than the negative one; a result consistent with Jochum (2000) and Kos and Todorovic (2008). The difference in survival probabilities between empirical and theoretical models (Random Walk and ARMA (1,1) process) is strongly statistically significant for momentums lasting up to eight months. Average empirical survival time of positive momentum across all portfolios is 4 months, while for negative momentum it is 3 months for small cap group of portfolios and 2 months for the large cap ones. Comparative analysis of average survival times using empirical data and benchmark model simulations shows that empirical survival time of positive momentum is underestimated by theoretical models; while it is marginally overestimated for negative momentum. This implies lesser ability of theoretical models to explain empirical price patterns on the positive momentum side, which leads us to more profitable positive momentum trading in our study. We show that long-only positive momentum is a feasible strategy for investors as the level of transaction costs that would make positive momentum trading unprofitable are much higher than what investors would be asked to pay in reality. Long-short strategies in our study show the most consistent risk-adjusted performance across portfolios and highest incremental Sharpe ratios relative to naïve buy and hold strategies. Finally, we show that survival probabilities are not significantly different across economic regimes in most of the portfolios, implying persistence in momentum strategies. Our trading rule results corroborate this as the performance of trading strategies is not very different across economic regimes. The results also hold during the recent financial crises and its aftermath, which is in contrast to evidence provided by Andrikopoulos et al. (2013). This shows that the KM estimator has a potential to be more powerful tool for designing a profitable momentum strategy than the approach based on pre-defined formation and holding periods (3, 6, 9, 12 months as per Jegadeesh and Titman,1993, for example), traditional in the momentum literature.

The remainder of the paper is organised as follows: Section 2 outlines the data and methodological framework; Section 3 discusses the findings and Section 4 provides conclusions to the paper and recommendations for further research.

2   Data and Methodological Framework

2.1   Data

This study utilizes monthly UK style factor portfolios data from Gregory, Tharyan and Christidis (2013) in the period October 1980 to June 2014. The data is a UK equivalent of the Fama-French's US market data[4] and is obtained from the Xfi Centre for Finance and Investment[5], University of Exeter. To form the portfolios, Gregory, Tharyan and Christidis (2013) sort the sample firms on market capitalisation into 'B'-big and 'S'-small and book-to-market ratio into 'H'-high and 'L'-low[6]. Six intersecting style portfolios are used in this study: SH; SM; SL; BH; BM; BL (where "SH" is the small size high book-to-market portfolio, "SL" is the small size low book-to-market portfolio, "BL" is the big size low book-to-market portfolio and so on). The portfolios are formed at the beginning of October in year '*t*' so we select October 1980 as the start of our sample period.

2.2   Methodological framework

3.1   Momentum signal

Let us provide definition of the momentum signal used in this study. Following Jochum (2000) and Kos and Todorovic (2008) we consider momentum a technical trading rule according to which a buy (sell) signal is triggered if a positive (negative) return is realised over two consecutive periods. Any returns of the same sign following immediately are then added to the duration of this momentum signal and a (positive or negative) trend is formed. We consider the trend to be broken if the return changes to the opposite sign. This definition implies that positive and negative momentum trends are not necessarily alternative of each other (Jochum, 2000). For each trend, the number of periods (months) it persisted is counted (e.g. 3, 4, 5 etc.) and the direction of the trend is taken into account. The Kaplan-Meier estimator uses this information to calculate the survival probability of a positive (negative) trend to last, say, 3 or 4 periods.

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[4]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[5]http://business-school.exeter.ac.uk/research/areas/centres/xfi/research/famafrench/files/ (Accessed on 20.07.15)
[6] For methodology refer to Gregory et. al (2013)

Empirical evidence shows that profitability of momentum strategies is wiped out by high transaction costs (see for instance Carhart, 1997). To successfully link the momentum survival probability to a trading rule feasible for investors, the trade-off between rigidness of momentum definition (in particular definition of what constitutes a break of trend) and transaction cost has to be considered (Kos and Todorovic, 2008). A more rigid definition of a trend change (as in our case - where a trend is broken if a return changes sign), will imply higher degree of transaction cost due to more frequent buy/sell decisions. By relaxing the trading rule and considering a trend change not only when the return changes sign but also when it goes over a predetermined threshold level – the transaction costs are likely to decrease. Note that the same definition of momentum signal and trend reversal/break will be applied to both actual style portfolio returns and simulated returns series, to ensure comparability.

Table 1 illustrates sequence of momentum signals and generation of trend. We define momentum as 1 in the table and no momentum as 0. For a positive trend, we identify two momentum signals, one surviving two months and one surviving three months. So the probability of three-month survival given two sequentials is 50%. For the negative trend, only one momentum signal lasting 1 period is identified, so the probability of even two period survival is zero.

Table 1: Return Changes and Trend Construction

The table shows illustration of trend construction. Rows show return changes, positive and negative trend respectively over the 10 months interval (columns). Momentum signal is triggered when a positive/negative return occurs over two consecutive periods. 1 in the table denotes a (positive or negative) momentum signal and 0 implies no momentum.

Month	1	2	3	4	5	6	7	8	9	10
Return Changes	0.013	0.009	0.041	-0.011	0.085	0.074	0.122	0.010	-0.013	-0.001
Positive Trend	0	1	1	0	0	1	1	1	0	0
Negative Trend	0	0	0	0	0	0	0	0	0	1

3.2 Survival Time Estimation

Survival analysis studies the time of survival or failure of an event/object (in our case - the momentum) and the probability of survival or failure in a given time period. Survival analysis originates in medical research studies, but it has been successfully applied in economics and

finance[7] in the context of duration analysis for instance. In the survival study, since the data are collected over a finite period of time, it is usual that time-to-event (survival time) may not be observed for all the individual of the study sample (or population), and thus their true time-to-event is unknown. These observations are called censored observations. The analysis of such time-to-event data with censoring characteristics cannot be handled properly by the standard statistical methods, but the survival analysis. This study, similar to Jochum (2000); and Kos and Todorovic (2008), focuses on the 'survival probabilities' as this best confine the intuition behind the financial concept of momentum. They are estimated by the Kaplan-Meier estimator, as described in the next section.

3.2.1 Kaplan-Meier Estimator

The survival probabilities can be estimated using Kaplan-Meier method, proposed by Kaplan and Meier (1958), from the observed survival time. The KM method (also known as product limit method) is non-parametric, hence no assumptions about the distribution of survival curve have to be made.

In the KM estimator, the momentum observations of the portfolios can be ordered in accordance to the duration of momentum survival (time-to-event). The estimator also gives the probabilities of those durations. Hence, the Kaplan-Meier estimator resembles the censored generalisation of the empirical distribution function.

The proportion of the observations which have survived to the first observed survival time t_1, $\hat{S}(t_1)$, is simply one minus the proportion of observation which have failed by the time t_1. The latter proportion can be estimated by the number of observations that have failed (momentum trends that were broken), d_1, divided by the number of observations which were at the risk of failure, n_1. That is, d_1/n_1. Similarly the proportion of momentums surviving to the second observed survival time t_2, $\hat{S}(t_2)$, is one minus the proportion of observations which failed between t_1 and t_2, multiplied by $\hat{S}(t_1)$; i.e. $S(t_2) = S(t_1)(1 - \frac{d_1}{n_1})$. The equation can be generalised as:

$$\hat{S}(t_j) = \prod_{j\,|\,t_t<t} (1 - \frac{d_j}{n_j})$$

(9)

Where, t_j= Ordered failure time. At $t = t_j$; $t(1) \leq t(2) \leq t(k)$

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[7] See for instance Kiefer (1988) and Jochum (2000) among others.

d_j= Number of failures at time $t = t_j$

n_j= Number of observations which are alive at time $t = t_j$, i.e. the observations at risk of exit.

Hence, the survival function of KM method is the product of one minus the 'failure rate' at each of the survival times. $S(t)$ is a constant between the time of events, and hence the estimated survival probably is a step function which changes only at each time when event occurs. Therefore, every step in the survival function represents the change in probability of momentum surviving beyond a given time horizon $t(j)$. This probability is conditional upon surviving, provided that the momentum is alive.

The standard error of K-M estimator at time t can be calculated as:

$$Std.Error = \sqrt{Var\left(\hat{S}(t)\right)} = \sqrt{\hat{S}^2(t) \sum_{t_t < t} \frac{d_j}{n_j(n_j - d_j)}} \tag{10}$$

3.3   Simulating Style Portfolio Returns

One of the objectives of this study is to assess whether theoretical models used in describing price behaviour can explain variations in empirical survival functions. To do so, empirical survival function for each of the six style portfolios is compared with simulated theoretical survival curves. The initial step of Monte-Carlo simulation is to formulate the model to be used for data simulation. Following Jochum, (2000) and Kos and Todorovic (2008) we apply simulation using Random Walk and Auto Regressive Moving Average (ARMA(1,1)); widely used models that describe stock return behaviour. Random walk is extensively analysed in efficient market literature since (Fama, 1965), while the ARMA (1,1) model is finds its support in Pagan (1996) and Fama and French (1988) among others.

According to Random Walk literature the market is not predictable and the price changes are independent of each other. Random walk model can be formulated as:

$$p_t = \mu + p_{t-1} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{11}$$

Here, μ is the drift constant, p_{t-1} is the lagged price and ε_t is the random error term.

ARMA model uses returns rather than prices and takes into account both the lagged value of the stock return and the random error term. An ARMA (1, 1) is a combination Auto

regressive (AR) process and Moving average (MA) process. Both AR and MA processes are based on the simple concept of random error or stochastic errors (shocks or innovations). A shock occurs between the two observations in a series and can affect the level of the series. ARMA model describes these shocks or disturbance of the time series data. AR process assumes that each value of the times series is a linear function of the lagged value(s) and a random shock. In MA process each value is determined by the average of current shocks or disturbance and lagged shocks. The order of moving average specifies the number of lagged shocks to be included in the model.

An ARMA (1, 1) is a combination of AR (1) and MA (1) process and can be defined as

$$r_t = \mu + \alpha_1 r_{t-1} + \beta_1 \varepsilon_{t-1} + \varepsilon_t \tag{12}$$

Where, r_t is the portfolio return, μ is constant and ε_t is the shocks or innovation of portfolio return and is a white noise, i.e. $E(\varepsilon_t) = 0$

In the second step of Monte-Carlo simulation we estimate the parameters of both Random-Walk and ARMA (1, 1) process for the period October 1980 to June 2014. 10,000 simulated time series of the same length as the empirical data are produced for six style portfolios. For each of the simulated series, the survival curve is obtained.

The comparison of empirical survival curves with theoretical (simulated) ones allows us to infer whether the survival of an existing trend (positive or negative) is higher or lower than the values gained from Random Walk with drift and ARMA (1,1). We compare the mean survival times of theoretical and empirical curves. In case of identical theoretical and empirical survival curves we expect that the market reflects all available information and there are less possibilities to exploit the discrepancies. However, if there are discrepancies between actual (empirical) survival time and theoretical survival time, we treat it as a sign of inefficiency as theoretical models are unable to fully capture the complexity of the empirical data. This would further imply that and one could employ simple momentum trading rules to generate higher returns using style portfolios. The trading rules applied in this study and their implementation is described in section 4.4 of the paper.

4   Empirical Results

4.1 Kaplan-Meier Estimator

The results of the step-wise calculation of Kaplan-Meier estimator for both positive and negative momentum are reported in Table 2 for Small Size and Low Book-to-Market (SL, i.e. small-growth) portfolio. To save space, tables showing results for the remaining five portfolios[8], are available in the appendix of the working paper version of this work[9]. Second column of each of the aforementioned tables represents ordered failure time, i.e. the number of consecutive months momentum has survived. We note that across all portfolios positive momentum survives longer than the negative, consistent with Jochum (2000) and Kos and Todorovic (2008). In Table 2, the maximum positive momentum sequential for SL portfolio is 11 months. The longest positive return sequential in our sample of portfolios lasts 14 months and is observed in SH and BH portfolios, reported in Tables A2 and A5 respectively. This is similar to the findings of Lewellen (2002) who observes that style portfolios exhibit momentum for up to 17 months. The longest negative return sequential has been identified for 9 months in SL portfolio in Table 2. Positive and negative return continuation over a horizon of 3 to 12 months is also reported in the study of Jegadeesh and Titman (1993).

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[8] Small Size & Medium BTM (SM), Small Size & High BTM (SH), Big Size & Low BTM (BL), Big Size & Medium BTM (BM), and Big Size & High BTM (BH)
[9] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2990275

Table 2: KM estimator of Small Size & Low book-to-market (SL) Portfolio

This table reports the stepwise calculation of Kaplan-Meier estimator for Small Size & Low book-to-market (**SL**) Portfolio. The survival function (S_t) proportion of observations which have survived to the time $t(j)$, where $t(1) \leq t(2) \leq t(k)$. n_j represents number of observations which are still alive at time $t = t_j$. d_j represents the number of momentum trends that have been broken at time $t = t_j$. The table also reports the standard error of the KM estimator. The survival function of both positive and negative momentum is reported.

j	Ordered failure time, $t(j)$	Intact before t (n_j)	Ending at time t (d_j)	Survivor function (S_t)	Stdandard Error $\sqrt{Var(S(t))}$
Survival Function of Positive Portfolio Momentum					
1	2	174	55	0.6839	0.0352
2	3	119	34	0.4885	0.0379
3	4	85	25	0.3448	0.0360
4	5	60	20	0.2299	0.0319
5	6	40	13	0.1552	0.0274
6	7	27	8	0.1092	0.0236
7	8	19	6	0.0747	0.0199
8	9	13	6	0.0402	0.0149
9	10	7	6	0.0057	0.0057
10	11	1	1	0.0000	-
Survival Function of Negative Portfolio Momentum					
1	2	71	36	0.4930	0.0593
2	3	35	16	0.2676	0.0525
3	4	19	9	0.1408	0.0413
4	5	10	5	0.0704	0.0304
5	6	5	2	0.0423	0.0239
6	7	3	1	0.0282	0.0196
7	8	2	1	0.0141	0.0140
8	9	1	1	0.0000	.

The third column of Table 2 shows the number of 'alive' momentums before ordered failure time, t(j). In the sample of 405 observations, 174 positive momentums that survive (n_j) for two months are identified. Out of those, 55 momentums (d_j, column 4) dies at 2 months. The remaining 119 momentums continue to survive for at least three months, where 34 observations die after three months of momentum etc. Only one momentum survived 11 months in Table 2. For negative momentum, out of 405 observations only 71 have been identified with two months of negative momentum, of which 36 of them die after two months etc.

The survival function (S_t) can be interpreted as the probability of trend continuation until failure time t(j) months conditioned upon the fact that the momentum is alive in t(j), where t(1)≤t(2)≤t(k). So for instance, the probability that the negative momentum survived at least 2 months is 49.30%; however, the probability of it surviving at least 3 months diminishes by almost 50% to 26.76%. Overall, our findings reveal that the probability of positive momentum surviving at least 2 successive months is 60% or more for all the portfolios. For negative momentum the equivalent probability is only 33% or more for all the portfolios. The standard error of Kaplan-Meier estimators are low for all the style portfolios such that the statistical significance of survival probabilities are not at risk.

4.2 Empirical vs. theoretical survival curves and scope for arbitrage

In this section, empirical momentum survival probabilities of style portfolios are compared with those of simulated theoretical benchmark curves. If the theoretical models fully explain the empirical momentum survival process, there should be no statistically significant difference between empirical and theoretical survival probabilities. Should the survival times of the empirical curves prove to be different 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 and that exploitable arbitrage opportunities exist.

Table 3 reports the survival function of theoretical survival curves (Monte-Carlo Simulation of Random Walk and ARMA (1,1) process) for both positive and negative momentum for SL portfolio. Equivalent tables for the remaining five portfolios can be found Table A1 in the appendix. We use t-test to signify the difference between theoretical and empirical survival functions of corresponding ordered failure time for both positive and negative momentum. To illustrate interpretation of Table 3, let us use ordered failure time of two periods. According to empirical survival curve, there is 68.39% probability that positive momentum will last for two months. Compared to the theoretical curves, probability of survival of positive momentum for two months according to random walk and ARMA (1,1) is considerably smaller at 50.26% and 56.94% respectively. The differences are significant 1% level. Empirical survival time of positive momentum of portfolio SL is up to 11 days, while the Random Walk model suggests it is up to 9 days; hence zeros in the table denote zero probability of momentum surviving in the corresponding ordered failure time.

Both Table 3 and A1 show that maximum survival time of positive momentums of simulated benchmark returns are lower than those for the empirical portfolios. The difference is by and large statistically significant across portfolios. In contrast, the negative momentums of simulated portfolios have longer survival times than empirical ones. However, this difference is not significant for portfolio SL (Table 3) and BL (Table A1, Panel C), while it is significant for shorter ordered failure times for the remaining portfolios in Table A1. Theoretical models are supposed to show us how market is behaving and fairly priced. If the survival probabilities of theoretical models are significantly different from empirical ones, there might be arbitrage opportunities to explore.

Table 3: Theoretical Survival Function for Small size and Low book-to-market (SL) portfolio

This table reports the survival function of theoretical survival curve (simulated Random Walk and ARMA (1,1) process) for SL portfolio. Empirical (KM) survival curve (Sj) is reported here for comparison purpose with theoretical survival curves. Simple t-test is performed to investigate whether the theoretical survival functions are identical to the positive or negative empirical survival functions of corresponding ordered failure time. P-value less than the significance level implies that the theoretical survival function is significantly different from their corresponding empirical function. Survival functions/probabilities are reported in decimal points. ***, ** and * imply the significance at 1%, 5% and 10% level of significance.

| Ordered failure time, $t(j)$ | Empirical (KM) Survival Function (Sj) | | Theoretical Survival Function | | | |
| | | | Random Walk | | ARMA(1,1) | |
	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum
2	0.6839	0.493	0.5026*** (0.0000)	0.4959 (0.9667)	0.5694*** (0.0101)	0.5675 (0.2769)
3	0.4885	0.2676	0.2461*** (0.0000)	0.2496 (0.7687)	0.3178*** (0.0002)	0.3223 (0.3716)
4	0.3448	0.1408	0.1188*** (0.0000)	0.1266 (0.7675)	0.1748*** (0.0000)	0.1784 (0.4374)
5	0.2299	0.0704	0.0582*** (0.0000)	0.0609 (0.7874)	0.0936*** (0.0002)	0.0974 (0.4523)
6	0.1552	0.0423	0.0257*** (0.0000)	0.0296 (0.6424)	0.047*** (0.0006)	0.0522 (0.7239)
7	0.1092	0.0282	0.0124*** (0.0003)	0.0118 (0.4543)	0.0235** (0.01426)	0.0261 (0.9261)
8	0.0747	0.0141	0.0048*** (0.001928)	0.0037 (0.4993)	0.0088*** (0.003)	0.0108 (0.8361)
9	0.0402	0	0	0	0	0.0014
10	0.0057					0.0007
11	0					0

Table 4 presents the mean survival time (restricted mean survival time) for the empirical (KM) as well as simulated (Random Walk and ARMA (1,1)) curves. The survival probability we have analysed in Tables 2 and 3, S(t) is given for the specific point in time 't' and is a summary measure. It does not, however, contain the information regarding the survival time distribution profile during the whole time interval (0, t). Mean survival time or restricted mean survival time is the useful alternative which summarizes the survival process using information beyond the survival probability only at a single time t, representing the area under the survival curve S(t) from period 0 to period t (Zhao et al., 2016; Royston and Parmar, 2013). Table 4 documents that in the case of positive portfolio momentum, the mean survival time given by theoretical Random Walk or ARMA (1,1) model is shorter than the empirical one; while the opposite is found for negative portfolio momentum.

Moreover, in support of findings from Table 2, estimated empirical mean survival for positive momentum is longer than that for the negative momentum. Positive momentum in style portfolios survives on the average around four months[10], while the negative average survival time is two or three months, depending on the portfolio. Kos and Todorovic (2008) point that Grinblatt, Titman and Wermers (1995) 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 stronger positive market momentum. These empirical findings suggest profit potentials for investors that can be exploited by adequate trading strategy.

Table 4: Empirical and Theoretical Mean Survival Times: Six Portfolio and Full Sample Period

This table reports the mean (average) survival time for the empirical (KM) as well as simulated (RW and ARMA) curve. The estimating period is October1980 to June 2014. Theoretical survival curves are calculated from the Monte-Carlo simulation of 10,000 time series. The mean survival time are calculated from corresponding survival curve of Kaplan-Meier estimator.

Portfolios	Mean Empirical (KM) Survival Time	Mean RW Survival Time	Mean ARMA Survival Time
Positive Portfolio Momentum			
Small Size & Low BTM (SL) Portfolio	4.132184	2.968687	3.234758
Small Size & Medium BTM (SM) Portfolio	4.172043	3.028482	3.236601
Small Size & High BTM (SH) Portfolio	4.281081	3.00712	3.232162
Big Size & Low BTM (BL) Portfolio	4.045977	2.989682	3.022612
Big Size & Medium BTM (BM) Portfolio	3.539394	3.022577	2.894845
Big Size & High BTM (BH) Portfolio	4.095808	2.981913	2.975143

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[10] The rounding is done to the nearest whole number

Negative Portfolio Momentum

Small Size & Low BTM (SL) Portfolio	3.056338	2.978084	3.27121
Small Size & Medium BTM (SM) Portfolio	2.438597	2.985441	3.226335
Small Size & High BTM (SH) Portfolio	2.693548	2.921293	3.197999
Big Size & Low BTM (BL) Portfolio	2.847458	2.974138	3.07943
Big Size & Medium BTM (BM) Portfolio	2.521739	2.92324	2.791115
Big Size & High BTM (BH) Portfolio	2.52	2.943633	2.975496

Overall, Table 4 suggests there is potential in exploiting momentum, particularly the positive momentum, given adequate trading strategy and feasible level of transaction costs. To assess the viability of these findings, we implement a simple trading rule as described in 4.3 and assesses the profitability of positive (long-only), negative (short-only) and combined (long-short) style portfolio momentum trading.

4.3   Trading Strategy Design, Profitability and Transaction Costs

We implement trading rules based on mean survival times of both positive and negative momentum for each of the six style portfolios. We estimate in-sample empirical mean survival times for positive and negative momentum for the period October 1980 to December 2000 for each of the six portfolios and report them in Table 5. The out-of-sample trading period is then 163 months, from January 2001 to July 2014.

The empirical mean survival times in the in-sample period (Table 5) are almost identical to those in the overall sample (Table 4). Positive momentum mean survival time is approximately four months for all the style portfolios. Negative momentum mean survival time for the small size portfolios (SL, SM and SH) is approximately three months; while that falls to two months for large size portfolios (BL, BM and BH).

Table 5: In-Sample Empirical Mean Survival Times for Six Style Portfolios

This table reports the empirical mean survival time of positive and negative momentum for six UK style portfolios (SL, SM, SH, BL, BM and BH) over the estimating period 1980M10 to 2000M12. These mean survival times are showing the number of months the momentum survives, and they are rounded up to the nearest whole number for the purpose of our trading strategies described in Sections 4.3.1-4.3.3 of the paper.

Portfolios	Positive Mean Empirical Survival Time	Negative Mean Empirical Survival Time
Small Size & Low BTM (SL) Portfolio	4.185185	2.888889
Small Size & Medium BTM (SM) Portfolio	4.278261	2.514286
Small Size & High BTM (SH) Portfolio	4.45082	2.6875
Big Size & Low BTM (BL) Portfolio	4.2	2.387097
Big Size & Medium BTM (BM) Portfolio	3.679245	2.384615
Big Size & High BTM (BH) Portfolio	4.486487	2.304348

To illustrate whether exploiting empirical momentum mean survival times from Table 5 is profitable at a feasible level of transaction costs, we design trading rules easily implementable by practitioners. In the case of positive momentum, we take a long position in the relevant *portfolio* if a positive momentum signal is triggered (see section 3.1 for description of momentum signal) and hold it for the mean survival time of four months. Whereas if the negative momentum is observed, we take a short position and hold it for two months if large cap portfolio and three months if small cap portfolio. If no momentum signal is observed, we invest in the risk-free asset, proxied by UK three month T-Bill. Based on these rules, we design four strategies: 1) Long-only based on positive momentum, 2) Short-only based on negative momentum, 3) Long positive/Short negative momentum and 4) Long in winner style (portfolio with highest positive momentum) and Short in loser style (lowest negative momentum portfolio). Note that the last strategy implies style rotation, i.e. that investor switches style portfolios over investment horizon.

The risk-adjusted profitability of the strategies vis-à-vis their respective buy-and-hold benchmark is measured by the Sharpe ratio. As a benchmark for strategies 1) - 3) we use the buy-and-hold of the corresponding style portfolio, while for strategy 4) the buy-and-hold of the FTSE All Share Index.

The importance of transaction costs for profitability of active strategies, particularly those active strategies based on frequent trading should not be neglected. For instance Lesmond et. al (2004) and Agyei-Ampomah (2007) show evidence that in traditional Jegadeesh and Titman (1993) approach to momentum transaction costs can be substantial, exceeding 50%

p.a. for 3 month formation and 1 month holding period strategy. Traditional Jegadeesh and Titman (1993) momentum approach from these studies is applied to individual stocks, whereby stocks periodically enter (drop from) the winner (loser) portfolios if they meet (do not meet) eligibility criteria. Such a change in portfolio composition can be large and as frequent as once per month. Our strategy differs from this in several ways. First, note that our study explores the length of momentum persistence and explores profitability of momentum in style portfolios (not in individual stocks). Second, the style portfolios are pre-built Fama-French small/large/value/growth portfolios. Fama-French portfolios are rebalanced once per year and our data does not provide the information on their turnover[11]. However, we believe that the level of turnover within Fama-French style portfolios themselves by and large does not affect our performance, but the turnover of our strategy (buying/selling those portfolios) does. Let us explain this further. In our trading strategies, our investor alternates between a style portfolio and the risk free rate over the 14 year period, holding (shorting) the style portfolio for the length of mean survival time if positive (negative) momentum is observed or alternatively investing in the risk free rate. If the same momentum signal is repeated at the expiry of the mean survival time (say 4 months), we simply continue holding (shorting) the style portfolio in question. Tables 6 and 7 below show that for long positive and short negative momentum strategy we have on average less than 30 switches (between the style portfolio and the risk free rate) over the 14 years, which implies approximately 2 switches per year. Each switch represents a change in the position from a portfolio to the risk free rate or vice versa. Hence, in our case, having two switches in a year implies that the first switch relates buying/selling the *whole* style portfolio (all its component stocks) and the second switch infers taking the opposite position, i.e. a round-trip transaction, giving us 100% turnover[12] per year (on average). Some of our strategies will incur more switches, resulting in turnover of up to 200% per year.

Further, given that rebalancing of Fama-French portfolios occurs once per year, only if we are invested in the portfolio (rather than risk free rate) at the time of rebalancing, our strategy turnover will increase by the value of turnover in the invested portfolio. If we use as a proxy for turnover in our large and small cap portfolios the yearly turnover of the MSCI UK Large cap index (5.52%)[13] and MSCI UK Small cap index (6.13%)[14], we can conclude that i) this

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[11] Information on individual portfolio constituents and turnover is not available in the Exeter (or Kenneth French's) database

[12] Following Agyei-Ampomah (2007): %Turnover = ½(%Dropouts+%New)

[13] https://www.msci.com/documents/10199/36e2b33b-0722-476f-9dbb-e4b30629e349

only marginally adds to our overall strategy turnover p.a. and ii) it adds to it *only when* we are invested the portfolio at the time of rebalancing. Hence, we consider this additional cost has a negligible impact on our main findings.

Let us go back to the fact that our long positive and short negative momentum strategies have a turnover of around 100%. The transaction costs for a UK large cap portfolio with 100% turnover are estimated to be 1.8% per year, while for a 200% turnover portfolio they are 3.1%[15]per year, according to Frontier Investment Management LLP research, and we will use those costs as a proxy for assessing the feasibility of trading in our discussion. For UK small cap portfolio transaction costs we will use as the proxy the US Small Cap portfolio costs of 2.5% per year, as in Bernstein (2000), as no equivalent UK figures were available.

To assess the feasibility of our strategies, we calculate the break-even level of transaction costs per trade for each portfolio. Those are maximum costs *per trade* that will equalise the Sharpe ratio of the momentum strategy to that of the buy-and-hold benchmark. The costs are deducted from the portfolio return in the months in which the trade occurs. Note that where we have 100% turnover per year in the strategy, the break-even cost per trade will be the same as the break-even cost per year[16]. In strategies where the turnover is greater, the break-even costs per trade will be converted into costs per year. The annualised breakeven transaction costs will then be compared to the threshold value of 1.8% for UK large cap portfolios and 2.5% for UK small cap portfolios as discussed above. If our breakeven transaction costs are higher than these thresholds, we consider the strategy feasible by investors. Please note that these threshold transaction costs are estimated per year, while our costs are calculates 'per trade' and in the sample period we have 2 or more trades every year. The mechanics, profitability and feasibility of each strategy are further discussed in the sub-sections that follow.

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[14] https://www.msci.com/documents/10199/5ee0d6b4-bd26-4c65-a42d-8cb012fe8604

[15] Figures correspond to 2007 research, and given the trend of decreasing transaction costs over the years they are likely to be lower in later years in our sample: http://www.frontierim.com/files/file/download/id/592

[16] Cost per year = turnover x cost per trade

4.3.1 Strategy 1) and 2): Long-only Positive Momentum and Short-only Negative Momentum in Each Portfolio

In the long-only positive momentum strategy we buy a style portfolio once the momentum signal is established and hold it for four months. In the short-only negative momentum we short a style portfolio once a negative momentum is triggered and hold it for three months if small cap and two months if large cap portfolio. When no momentum is observed, both strategies assume investment in UK three month T-bill. The strategies are applied in each portfolio separately.

Tables 6 and 7 report annualised mean return, standard deviation, Sharpe ratio, the number of switches over the trading period and break-even transaction costs per switch for each of the style portfolios and for positive and negative momentum respectively. Comparative figures (where applicable) are reported for the buy and hold portfolios.

The results in table 6 reveal that applying long-only positive momentum strategy results in higher returns and Sharpe ratios in all style portfolios, at a feasible level of transaction costs (compared to 1.8% threshold for large cap and 2.5% threshold for small cap portfolios as discussed in section 4.3). Exploiting positive momentum is most profitable in SH (small-value) portfolio, generating Sharpe ratio of 1.23 and breakeven level of transaction costs of 4.44% per trade. This means that style momentum trader can pay up to 4.44% transaction costs per trade and still generate higher Sharpe ratio than the buy and hold of the SH portfolio. We also show that positive momentum trading has lower standard deviation than the buy-and-hold strategy for all the portfolios.

In contrast, Table 7 shows that although strategy based on negative portfolio momentum has lower risk than the corresponding buy-and-hold, only portfolios SL and BL outperform the buy-and-hold strategy at a level of breakeven transaction costs above the threshold of 2.5% for small and 1.8% for large portfolios. This is not surprising because theoretical negative momentum survival curves are almost identical with the empirical curves for most portfolios. Hence there are less possibilities to exploit the market using the negative momentum.

In general, results for the positive momentum effects are more pronounced than negative momentum effects. The results also suggest that the model works well for both positive and negative momentum where the empirical survival curves are not identical with theoretical

survival curves. Hence, the survivorship model can be seen as a compelling indicator of profitable trades.

Table 6: Trading Rule Results of Positive Portfolio Momentum

For each of the six UK style portfolios (SL, SM, SH, BL, BM and BH) the table reports annualised mean return, standard deviation and Sharpe ratio of the Long only trading strategy that alternates between investing in a style portfolio if positive momentum is observed or in the UK 1 month T-bill otherwise. The same is reported for the buy and hold strategy (long position in each portfolio). No. of switches represents the number of times we switch between the portfolio and the T-bill in the long-only strategy. Two switches is equivalent to one round trip transaction. Break-even transaction costs (TC) represent the maximum cost (in basis points, BPS) an investor can pay *per switch (trade)* and still perform as well as the buy and hold strategy. Trading period: January 2001 to June 2014.

	Small Size & Low BTM (SL) Portfolio		Small Size & Medium BTM (SM) Portfolio		Small Size & High BTM (SH) Portfolio	
	Buy and Hold	Long Only Strategy	Buy and Hold	Long Only Strategy	Buy and Hold	Long Only Strategy
Mean Return	4.00	12.81	12.17	18.80	10.98	21.05
Std. Dev.	19.85	14.01	17.84	12.45	20.37	14.12
Sharpe Ratio	0.16	0.73	0.58	1.22	0.48	1.23
No. of Switches	-	29	-	31	-	32
Break Even TC	-	375.87 BPS	-	337.78 BPS	-	444.65 BPS

	Big Size & Low BTM (BL) Portfolio		Big Size & Medium BTM (BM) Portfolio		Big Size & High BTM (BH) Portfolio	
	Buy and Hold	Long Only Strategy	Buy And Hold	Long Only Strategy	Buy and Hold	Long Only Strategy
Mean Return	5.06	11.79	6.97	13.26	6.12	11.94
Std. Dev.	12.17	7.72	16.46	10.65	17.34	12.10
Sharpe Ratio	0.23	1.12	0.32	0.96	0.27	0.76
No. of Switches	-	24	-	32	-	31
Break Even TC	-	372.17 BPS	-	284.32 BPS	-	263.65 BPS

Table 7: Trading Rule Results of Negative Portfolio Momentum

For each of the six UK style portfolios (SL, SM, SH, BL, BM and BH) the table reports annualised mean return, standard deviation and Sharpe ratio of the Short only trading strategy that alternates between investing in a style portfolio if negative momentum is observed or in the UK 1 month T-bill otherwise. The same is reported for the buy and hold strategy (long position in each portfolio). No. of switches represents the number of times we switch between the portfolio and the T-bill in the short-only strategy. Two switches is equivalent to one round trip transaction. Break-even transaction costs (TC) represent the maximum cost (in basis points, BPS) an investor can pay *per switch (trade)* and still perform as well as the buy and hold strategy. Trading period: January 2001 to June 2014.

	Small Size & Low BTM (SL) Portfolio		Small Size & Medium BTM (SM) Portfolio		Small Size & High BTM (SH) Portfolio	
	Buy and Hold	Short Only Strategy	Buy and Hold	Short Only Strategy	Buy and Hold	Short Only Strategy
Mean Return	4.00	11.65	12.17	6.97	10.98	6.83
Std. Dev.	19.85	13.20	17.84	11.67	20.37	14.55
Sharpe Ratio	0.16	0.69	0.58	0.40	0.48	0.34
No. of Switches	-	31	-	27	-	29
Break Even TC	-	305.04 BPS	-	Negative	-	Negative

	Big Size & Low BTM (BL) Portfolio		Big Size & Medium BTM (BM) Portfolio		Big Size & High BTM (BH) Portfolio	
	Buy and Hold	Short Only Strategy	Buy and Hold	Short Only Strategy	Buy and Hold	Short Only Strategy
Mean Return	5.06	8.98	6.97	7.56	6.12	4.94
Std. Dev.	12.17	7.21	16.46	8.39	17.34	9.84
Sharpe Ratio	0.23	0.86	0.32	0.58	0.27	0.25
No. of Switches	-	23	-	24	-	35
Break Even TC	-	257.44 BPS	-	127.39 BPS	-	Negative

4.3.2 Strategy 3): Long Positive/Short Negative Momentum in Each Portfolio

This strategy is a combination of strategy 1) and 2) for each portfolio. Hence, the long (short) position in the relevant portfolios involves buying (shorting) that portfolio if a positive (negative) momentum is observed and holding it according to mean survival time. Note that we never engage in the long and short position at the same time in this strategy, but we alternate them. The performance and feasibility of the strategy are presented in Table 8, where we report the Sharpe ratios and break-even transaction costs of the strategy and the buy-and-hold of each relevant portfolio. Our long-short strategy in each portfolio separately significantly outperforms the respective buy-and-hold benchmarks. The highest Sharpe ratio of large-growth (BL) long-short momentum strategy is 1.42, which is more than six times that of the corresponding buy-and-hold. The level of breakeven transaction costs that equalises the Sharpe ratio of this long/short strategy to that of the buy and hold is very high,

at 367.09 bps. Hence, as long as one pays less than 3.67% per each switch, they will outperform the buy-and-hold, which is verifying the feasibility of our strategy. Note that in this long/short strategy, there is 3-4 switches per year (ranging from 40-51 over 14 years across portfolios), corresponding to 150-200% portfolio turnover as two switches indicates one round-trip transaction. Assuming more extreme 200% as annual turnover for the purpose of this discussion, our investor can afford to pay transaction costs of up to 7.34% (=2 x 3.67%) per year and still outperform the buy-and-hold strategy. As per our earlier discussion, UK large cap portfolios with 200% turnover have estimated transaction costs of 3.1% per year, implying that outperformance with our style momentum strategy is easily achievable for investors. The trading costs of small cap portfolios with 200% turnover[17] will be higher than 3.1% but they are unlikely to be as high as the break-even value of 7.34%.

Table 8: Long Positive/Short Negative momentum in each style portfolio

For each of the six UK style portfolios (SL, SM, SH, BL, BM and BH) the table reports annualised mean return, standard deviation and Sharpe ratio of the Long Positive/Short Negative momentum trading strategy that combines a long position if positive momentum in a portfolio is observed and a short position if negative momentum in a portfolio is observed, giving us a Long Positive/Short Negative momentum strategy. The same is reported for the buy and hold strategy (long position in each portfolio). No.of switches represents the number of times we switch between the long, the short position and the T-bill. Two switches is equivalent to one round trip transaction. Break-even transaction costs (TC) represent the maximum cost (in basis points, BPS) an investor can pay *per switch (trade)* and still perform as well as the buy and hold strategy. Trading period: January 2001 to June 2014.

	Small Size & Low BTM (SL) Portfolio		Small Size & Medium BTM (SM) Portfolio		Small Size & High BTM (SH) Portfolio	
	Buy and Hold	Long/Short Strategy	Buy and Hold	Long/Short Strategy	Buy and Hold	Long/Short Strategy
Mean Return	4.00	7.85	12.17	10.77	10.98	10.68
Std. Dev.	19.85	9.19	17.84	7.68	20.37	9.01
Sharpe Ratio	0.16	0.56	0.58	1.00	0.48	0.87
No. of Switches	-	51	-	40	-	47
Break Even TC	-	199.93	-	226.98	-	205.05

	Big Size & Low BTM (BL) Portfolio		Big Size & Medium BTM (BM) Portfolio		Big Size & High BTM (BH) Portfolio	
	Buy and Hold	Long/Short Strategy	Buy and Hold	Long/Short Strategy	Buy and Hold	Long/Short Strategy
Mean Return	5.06	10.09	6.97	10.33	6.12	10.27
Std. Dev.	12.17	4.93	16.46	6.25	17.34	6.68
Sharpe Ratio	0.23	1.42	0.32	1.15	0.27	1.08
No. of Switches	-	42	-	51	-	46
Break Even TC	-	367.09	-	276.35	-	318.26

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[17] The estimated size of these costs is unavailable to us

4.3.3 Strategy 4): Long Winner/Short Loser Portfolio Style Rotation Strategy

This strategy implies buying the winner portfolio (a portfolio with highest positive momentum) in month t and holding it for the mean survival time of four months, t+3. Once the four-month holding period expires, in month t+4 we identify a portfolio with the next positive momentum trigger. If more than one portfolio exhibits momentum signal in the same month, we buy the one with the highest positive momentum. We roll this on until the end of the trading period, 163 months in total. The strategy also involves simultaneously shorting a loser portfolio (a style portfolio that has the lowest negative momentum) in month t. We hold the short position for the average negative momentum survival time (two months for large or three months for small cap portfolios). Once the short position is closed, similarly to the winner leg of the strategy, we search for the next loser style portfolio to short. In months when we are neither long nor short, the investment is in the UK T-bill.

During the trading period, there is 61 'buy' and 59 'sell' signals. Over 14 years, this relates to 8.6 switches per year or 4.3 round-trips, making turnover 430% on average in this strategy. Most traded portfolio is small-growth (SL) with 34 buy/sell signals and the least traded one is SM with 4 signals. Note that we are not long (or short) in more than one portfolio at the time, but we can be short in one and long in another portfolio at the time t[18]. Hence, this results in style rotation strategy. Such rotation across investment styles causes inconsistent risk parameters in a portfolio; which does not comply with traditional mutual fund risk constraints. For this reason, style rotation strategies are more suitable for hedge funds than for funds pursuing more traditional, long-only, approach to investing. Style rotation applied in the context of momentum investing is found to be profitable in the UK in Clare, Sapuric and Todorovic (2010)[19] for instance.

Table 9 reports the results of the long winner/short loser style rotation strategy, including both the (long) winner and (short) loser trading results separately. We show annualised mean return, standard deviation and Sharpe ratio of the strategy and the buy-and-hold of the benchmark. As the benchmark, we chose FTSE All Share index, as a representative index for the UK market given that we switch across portfolios representing various segments of the market.

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[18] Also, note that we do not allow the long and the short position to be in the same portfolio.

[19] A number of other papers documents profitability of style rotation strategies in the UK (Levis and Liodakis (1999) and Levis and Tessaromatis (2004) and the US (Kao and Shumaker (1999); Arshanapalli, Switzer and Panju (2007) among many others)

Table 9: Winner/Loser Style Rotation

This table reports the annualised Mean Return, Standard Deviation, Sharpe Ratio and break-even transaction costs (in basis points, BPS) of winner/loser momentum trading. Long Winner (Short Loser) Style rotation implies long position (short position) in the portfolio with the highest positive (lowest negative) momentum in month t. If the positive (negative) momentum is not observed, we invest in UK three month T-Bill. Long winner/short loser strategy is the combination of the Long Winner and Short Loser style rotation. Buy-and-hold is the FTSE All Share index. Trading period: January 2001 to June 2014.

	Mean Return (%)	Std. Dev (%)	Sharpe Ratio	Break-even TC
Long Winner Style Rotation	20.24	16.29	1.04	304.60 BPS
Short Loser Style Rotation	19.42	13.18	1.21	145.57 BPS
Long Winner/short loser Style Rotation	20.63	8.76	1.89	216.61 BPS
Buy-Hold of FTSE All Share	4.90	14.62	0.21	

The long winner/short loser strategy annualised mean return in Table 9 is around four times higher (20.63%) than that of the FTSE index (4.90%), with nearly 6% lower standard deviation, making the strategy's annualised Sharpe ratio (1.89) nine-times that of the index (0.21). Both the long and the short segment of the strategy separately generate considerably higher Sharpe ratios than the buy-and-hold. Breakeven transaction costs that equalise Sharpe ratio of the strategy to that of the FTSE All Share index buy-and-hold are at a feasible level for investors. The break-even costs are given *per trade*, implying that our investor can afford to pay up to 4.3 times the figures reported in Table 9 (as the average turnover is 430%) and still perform better than the buy-and-hold.

4.4 Survival Across Business Cycles

Stambaugh et. al (2012) and Avramov et al. (2016) show that the strength of momentum profits varies over time. In addition, there is evidence that momentum in the UK exhibits a degree of cyclical behaviour (see Sarwar et. al, 2016). Given this evidence, it is possible that the power of momentum and hence momentum profits in the UK style portfolios could be different across varying economic and market conditions. To assess this, we use the Log-rank and Wilcoxon tests, proposed by Peto et al. (1977), to test the null hypothesis that the momentum survival curves for style portfolios are identical across business cycles. Log Rank test is more sensitive than the Wilcoxon test to differences between groups in later points in time. Whereas, Wilcoxon test is more sensitive than the log-rank test to differences between groups that occur in early points in time.

Table 10 reports that the null hypothesis of the equality of empirical survivor functions across business cycles. In Table 10, 1 indicates recession and '0' indicates expansion periods. To differentiate between recession and expansion periods we use OECD based Recession Indicators for the United Kingdom taken from Federal Reserve Bank of St. Louis[20]. In Panel A, only SM and BH portfolios exhibit significantly unequal survival function over economic regimes according to both Long rank and Wilcoxon test. The momentum survival curve of SH and BM portfolios are found to be significantly unequal using Log-rank test, however this is rejected by Wilcoxon test. BL and SL portfolios do not exhibit cyclical differences in momentum survival curves. Reverting the analysis to negative momentum, the survival curves are different across economic regimes only for BM portfolio leading us to conclude that, overall, there is no strong evidence that style portfolios have different momentum survival time under different market conditions.

Table 10: Equality of Empirical Survival Function

Log rank and Wilcoxon test is performed to check whether or not the survival functions are similar across the business cycles. The economics regimes are the OECD based Recession Indicators for the United Kingdom taken from Federal Reserve Bank of St. Louis. 1 indicates recession and '0' indicates expansion periods. ***, ** and * imply the significance at 1%, 5% and 10% level of significance. Results are reported for each of the six portfolios for positive momentum (Panel A) and negative momentum (Panel B) separately.

	Economic Regimes	Log Rank Test (χ^2)	Wilcoxon Text (χ^2)
Panel A: Positive Portfolio Momentum			
SL	0	0.41	1.97
	1	(0.5223)	(0.1607)
SM	0	17.24***	14.17***
	1	(0.0000)	(0.0002)
SH	0	3.09*	2.22
	1	(0.0789)	(0.1365)
BL	0	0.24	0.00
	1	(0.6250)	(0.9679)
BM	0	3.71*	1.24
	1	(0.0541)	(0.2662)
BH	0	9.45***	4.91**
	1	(0.0021)	(0.0268)
Panel B: Negative Portfolio Momentum			
SL	0	1.46	0.08
	1	(0.2265)	(0.7784)
SM	0	0.19	0.02
	1	(0.6654)	(0.8909)
SH	0	0.84	0.84
	1	(0.3592)	(0.3600)
BL	0	0.34	0.16
	1	(0.5578)	(0.6873)
BM	0	3.33*	2.98*
	1	(0.0680)	(0.0843)
BH	0	0.16	0.01
	1	(0.6917)	(0.9043)

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[20] For the procedure visit: https://fred.stlouisfed.org/series/GBRRECDM

Given this evidence, one can infer that momentum strategies in style portfolios whose survival curve is statistically the same across economic cycles are expected to exhibit similar profitability irrespective of the economic regimes. That is, one can trade on either positive or negative momentum utilising its survival time without being concerned about the recession or expansion state of the market. We test this assumption during the trading period January 2001 to June 2014 where there is 51% of peak and 49% of trough months in the UK economy. To save space, we present profitability across economic cycles for long winner/short loser style rotation strategy only[21].

Table 11: Winner/Loser Style Rotation Across Business Cycles

This table reports the annualised Mean Return, Standard Deviation, Sharpe Ratio and break-even transaction costs (in basis points, BPS) of winner/loser momentum trading. The switching between portfolios is determined by two criteria: long position in the portfolio with the highest positive momentum and short position in the portfolio lowest negative momentum in month t. If the positive (negative) momentum is not observed we invest in UK three month T-Bill. Buy-and-hold is the FTSE All Share index. The economic regimes are the OECD based Recession Indicators for the United Kingdom taken from Federal Reserve Bank of St. Louis.

Panel A: Recession

	Mean Return (%)	Std. Dev (%)	Sharpe Ratio	Break-even TC
Winner/loser Style Rotation Long Winner	15.91	15.72	0.4676	404.53 BPS
Winner/loser Style Rotation Short Loser	23.14	14.82	0.7708	256.50 BPS
Winner/loser Style Rotation Long-Short	20.23	9.58	0.9397	272.28 BPS
Buy-Hold of FTSE All Share	-1.01	14.73	-0.2603	

Panel B: Expansion

Winner/loser Style Rotation Long Winner	24.97	16.88	0.7225	212.25 BPS
Winner/loser Style Rotation Short Loser	15.64	11.22	0.5681	49.12 BPS
Winner/loser Style Rotation Long-Short Loser	21.07	7.87	1.0967	143.38 BPS
Buy-Hold of FT All Share	11.49	14.38	0.2970	

Earlier in this study, Table 9 has shown that both long and short segment of the winner/loser style rotation strategy separately generate considerably higher Sharpe ratios than the buy-and-hold in the overall trading period January 2001 to June 2014. Consistent with what one would expect intuitively, Table 11 shows that in the recessions it pays more to be short, while in expansions the long side of the portfolio has the edge. Nevertheless, in both expansion and recession, the highest Sharpe ratios (well above those of the FTSE All Share index) are

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[21] Note that the remaining strategies presented in this paper lead to the same qualitative conclusions.

generated by the long winner/short loser strategy. Investors can pay transaction costs up to 2.7% *per trade* in recessions (1.4% in expansions) and still generate better performance than FTSE All Share benchmark. Hence, regardless of the economic state, our momentum strategies continue to generate strong risk-adjusted performance at a feasible level of transaction costs.

4.5. Surviving the Financial Crisis

In this section we present the results of trading based on our mean momentum survival time methodology in the sub − sample period from November 2007, which Bank of St. Louis database marks as the start of the UK crisis period, to the end of the sample in June 2014. Mean survival times are estimated for the in-sample period January 1980-October 2007. The mean survival time of positive momentum is 4 months across portfolios and the mean negative momentum survival time of SL, SM, SH, BL, BM and BH portfolios are 3, 2, 3, 3, 2, and 3 months respectively. The same long-only, short-only and long-short strategies used previously in this paper are applied. The buy-and-hold strategy, as before, represents the investment in each of the relevant portfolios.

Table 12: Trading Rules from the beginning of Recession (2007M11 to 2014M06)

The table reports annualised mean return, standard deviation, Sharpe ratio, number of switches and the break-even transaction costs (TC) for three different trading strategies and the buy-and hold over the trading period 2007M11 to 2014M06. The results are reported for each of the six portfolios separately (SL, SM, SH, BL, BM, BH). Long positive momentum strategy takes a long position in the portfolio if a positive momentum is observed, otherwise invests in T-Bill. Short negative momentum strategy takes a short position in the portfolio if a negative momentum is observed, otherwise invests in T-Bill. Long Positive-Short negative strategy is the combination of the two. The buy-and-hold strategy represents the investment in each of the six portfolios. No.of switches represents the number of times we switch between the long, the short position and the T-bill. Two switches is equivalent to one round trip transaction. Break-even transaction costs (TC) represent the maximum cost (in basis points, BPS) an investor can pay *per switch (trade)* and still perform as well as the buy and hold strategy. Trading period: November 2007- June 2014.

Portfolio	Trading Strategies	Mean Return	Std. Dev.	Sharpe Ratio	No. of Switches	Break Even TC
Small Size & Low BTM (SL)	Long Positive Mom	20.18	12.45	1.45	14	527.75 BPS
	Short Negative Mom	5.43	10.78	0.44	13	Negative
	Long Pos.-Short Neg. Mom	13.02	7.16	1.60	27	363.65 BPS
	Buy and Hold	9.46	17.97	0.53	-	-
Small Size & Medium BTM (SM)	Long Positive Mom	20.63	12.31	1.49	14	526.15 BPS
	Short Negative Mom	7.46	11.01	0.61	16	Negative
	Long Pos.-Short Neg. Mom	14.27	7.68	1.63	30	363.70 BPS
	Buy and Hold	9.91	19.40	0.53	-	-
Small Size & High BTM (SH)	Long Positive Mom	20.36	16.20	1.15	12	833.92 BPS
	Short Negative Mom	3.60	18.44	0.23	17	8.65 BPS
	Long Pos.-Short Neg. Mom	12.92	8.63	1.33	29	433.33 BPS
	Buy and Hold	3.52	24.17	0.22	-	-
Big Size & Low BTM (BL)	Long Positive Mom	12.15	8.55	1.25	10	299.40 BPS
	Short Negative Mom	1.44	6.80	0.08	11	Negative
	Long Pos-Short Neg Mom	6.85	5.05	1.12	21	Negative
	Buy and Hold	9.53	12.47	0.70	-	-
Big Size & Medium BTM (BM)	Long Positive Mom	11.54	9.88	1.03	15	335.67 BPS
	Short Negative Mom	8.81	8.47	0.92	10	372.64 BPS
	Long Pos-Short Neg Mom	10.43	5.74	1.56	25	389.30 BPS
	Buy and Hold	4.35	18.32	0.26	-	-
Big Size & High BTM (BH)	Long Positive Mom	10.64	12.40	0.78	14	329.82 BPS
	Short Negative Mom	1.33	12.45	0.08	15	Negative
	Long Pos-Short Neg Mom	6.40	7.43	0.73	29	169.40 BPS
	Buy and Hold	3.63	17.78	0.22	-	-

The results in this table are overall consistent with the ones reported for the whole sample period in Tables 6-8. Trading on positive momentum is profitable for transaction costs per trade up to 5.3%-8.3% for various small cap portfolios and up to 3%-3.3% per trade for

various large cap portfolios. With the exception of BM portfolio trading, the short-only strategy does not pay off. The long-short strategy generates highest Sharpe ratios in most portfolios. Similar as before, the turnover for long-only and short-only strategy is on average 100% p.a. (around 2 switches per year or 1 round-trip) and on average 200% p.a. for the long/short strategy. Given the threshold levels of transaction costs per year discussed in section 4.3. and annual turnover levels, all strategies that outperform buy-and-hold do so at a realistic level of transaction costs.

Table 13 illustrates the winner/loser style rotation strategy in the sub-sample period covering financial crisis from November 2007 to the end of the sample in June 2014. The long only, short only and long short rotation strategies all generate Sharpe ratios at least double that of that of the FTSE All Share buy and hold strategy. This is in contrast to Andrikopoulos et al. (2013) who find momentum to be an unprofitable strategy since the start of financial crisis of 2007/08[22]. The feasibility of long only strategy is better than that of short only and long short, indicating that as long investors pay less than 2.86% of transaction costs per trade, they will still generate greater Sharpe ratio than the buy-and-hold. The breakeven transaction costs figures for short-only and long-short strategy are lower at 0.61% and 1.67%, making the scope for outperformance narrower and less realistic, given the average UK portfolio trading costs.

Table 13: Winner/Loser Style Rotation after the Recession

The table reports annualised mean return, standard deviation, Sharpe ratio, number of switches and the break-even transaction costs (TC) of winner/loser style rotation momentum trading over the trading period 2007M11 to 2014M06. The switching between portfolios is determined by two criteria: long position in the portfolio with the highest positive (negative) momentum and short position in the portfolio with the lowest negative momentum in month t. If the positive (negative) momentum is not observed we invest in UK three month T-Bill. Buy-and-hold is the FTSE All Share index.

	Mean Return (%)	Std. Dev (%)	Sharpe Ratio	Break-even TC
Winner/loser Style Rotation Long	17.00	17.28	0.93	285.49 BPS
Winner/loser Style Rotation Short	10.22	16.56	0.60	60.69 BPS
Winner/loser Style Rotation Long-Short	14.97	9.64	1.39	166.43 BPS
Buy-Hold of FTSE All Share	4.34	16.09	0.27	-

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[22]The differences in findings may stem from the fact that their study uses daily data to construct momentum returns, they do not exploit momentum survival times but rather rebalance in regular intervals and their sample ends on 18th February 2010.

5   Conclusions

This study contributes to the literature of style momentum by studying the survival time of the momentum in UK style portfolios. Using the Kaplan-Meier method, we estimate momentum survival times for six UK portfolios, equivalents of the US Fama-French size and style portfolios in the period January 1980-July 2014. Consistent with the findings of Jochum (2000) and Kos & Todorovic (2008), we report that positive momentum survives longer than negative momentum. The estimated mean survival time of positive momentum is 4 months across the six portfolios, whereas the mean survival of negative momentum varies from 2 months for large cap portfolios to 3 months for small cap portfolios. We apply four simple trading strategies to exploit mean momentum survival times based on these empirical findings: long only positive momentum in each style portfolio; short only negative momentum in each style portfolio; long positive/short negative momentum in each style portfolio; and long winner/short loser portfolio − a style rotation strategy based on investing in portfolios with highest positive or lowest negative momentum. With the exception of the short only negative momentum, all strategies perform better than their buy and hold benchmarks and a feasible level of transaction costs. This is not surprising as the theoretical survival curves are almost identical with the empirical ones of the negative momentum across our style portfolios, indicating more market efficiency and less scope for profitable trading. Strongest performance, in terms of incremental Sharpe ratios relative to buy-and-hold is detected in long winner/short loser strategy, contributing to the evidence that style rotation strategies are profitable in the UK; a finding consistent with Clare, Sapuric and Todorovic (2010). This paper also looks at differences in survival times and performance of strategies across economic regimes. We document that momentum trading based on survival times works well in both recessions and expansions, as well as during recent financial crisis.

Our findings have useful implications for both traders and portfolio managers in that 1) the momentum in style portfolios in the UK is present; 2) the momentum survival time can be successfully exploited in each style portfolio separately (relevant for consistent style investors); 3) the momentum survival time leads to profitable trading in style rotation strategy (relevant for hedge fund managers) and 4) momentum trading based on mean survival times is feasible when accounting for costs. One of the limitations of the study is that the trading strategies are applied on the monthly data frequency (typical of momentum trading) but that implies rounding of our mean survival times to say four months, whereas actual survival time estimated may have been 4.3 months. Additionally, the length of momentum survival may be

impacted by some macroeconomic conditions and may vary over time. Hence, this study could be extended to look into the (macroeconomic or market) factors that may have an impact on the length of momentum survival time.

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Table A1: Theoretical Survival Function

This table reports the survival function of theoretical survival curves (simulated Random Walk and ARMA (1,1) process) for SM (Panel A), SH (Panel B), BL (Panel C), BM (Panel D) and BH (Panel E) portfolio. Empirical (KM) survival curve (Sj) is reported here for comparison purpose with theoretical survival curves. Simple t-test is performed to investigate whether the theoretical survival functions are identical to the positive or negative empirical survival functions of corresponding ordered failure time. P-value less than the significance level implies that the theoretical survival function is significantly different from their corresponding empirical function. Survival functions/probabilities are reported in decimal points. ***, ** and * imply the significance at 1%, 5% and 10% level of significance.

Ordered failure time, $t(j)$	Empirical Survival Function		Theoretical Survival Function			
			Random Walk		ARMA(1,1)	
	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum
Panel A: Small Size & Medium book-to-market **(SM)** Portfolio						
2	0.6882	0.3333	0.5142*** (0.0001)	0.4925** (0.0284)	0.5677*** (0.0054)	0.5577*** (0.0018)
3	0.4785	0.0877	0.2653*** (0.0000)	0.2542*** (0.0003)	0.3198*** (0.0005)	0.3135*** (0.0000)
4	0.3441	0.0175	0.1358*** (0.0000)	0.1327*** (0.0000)	0.1749*** (0.0001)	0.1772*** (0.0000)
5	0.2473	0	0.0671*** (0.0000)	0.0645	0.0938*** (0.0000)	0.0957
6	0.172		0.0304*** (0.0000)	0.0287	0.049*** (0.0001)	0.0512
7	0.1183		0.0121*** (0.0001)	0.0104	0.0226*** (0.0004)	0.0235
8	0.0699		0.0035*** (0.0016)	0.0025	0.0088*** (0.0038)	0.0075
9	0.0376		0	0	0	0
10	0.0108					
11	0.0054					
12	0					

Table A1 (Continued)

Ordered failure time, $t(j)$	Empirical Survival Function		Theoretical Survival Function			
			Random Walk		ARMA(1,1)	
	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum
Panel B: Small Size & High book-to-market (**SH**) Portfolio						
2	0.6919	0.4355	0.5032*** (0.0000)	0.4826 (0.5200)	0.5598*** (0.0023)	0.5616* (0.0808)
3	0.4865	0.1774	0.2563*** (0.0000)	0.2357 (0.3075)	0.311*** (0.0001)	0.3087** (0.0216)
4	0.3459	0.0645	0.1294*** (0.0000)	0.1139 (0.1906)	0.1722*** (0.0000)	0.168*** (0.0067)
5	0.2432	0.0161	0.0676*** (0.0000)	0.0543* (0.0647)	0.0958*** (0.0001)	0.0883*** (0.0008)
6	0.173	0	0.032*** (0.0000)	0.0232	0.0543*** (0.0003)	0.0435
7	0.1243		0.0138*** (0.0001)	0.0087	0.028*** (0.0006)	0.0204
8	0.0865		0.0047*** (0.0005)	0.0029	0.011*** (0.0012)	0.0076
9	0.0595		0	0	0	0
10	0.0324					
11	0.0216					
12	0.0108					
13	0.0054					
14	0					
Panel C: Big Size & Low book-to-market (**BL**) Portfolio						
2	0.6552	0.4576	0.5056*** (0.0012)	0.4988 (0.5818)	0.5146*** (0.0022)	0.5204 (0.4000)
3	0.4425	0.2034	0.2544*** (0.0001)	0.2429 (0.5167)	0.262*** (0.0001)	0.2698 (0.2765)
4	0.3161	0.1186	0.127*** (0.0000)	0.1203 (0.9720)	0.1329*** (0.0000)	0.142 (0.6324)
5	0.2184	0.0508	0.0595*** (0.0000)	0.0619 (0.7399)	0.0647*** (0.0000)	0.0764 (0.4479)
6	0.1437	0.0169	0.029*** (0.0002)	0.0317 (0.4670)	0.032*** (0.0003)	0.0405 (0.2533)
7	0.1092	0	0.0115*** (0.0003)	0.0137	0.0133*** (0.0003)	0.0191
8	0.0747		0.0028*** (0.0012)	0.0047	0.0031*** (0.0013)	0.0071
9	0.046		0	0	0	0.0004
10	0.0287					0
11	0.0115					
12	0					

Table A1 (Continued)

Ordered failure time, $t(j)$	Empirical Survival Function		Theoretical Survival Function			
			Random Walk		ARMA(1,1)	
	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum	Positive Momentum	Negative Momentum
Panel D: Big Size & Medium book-to-market (**BM**) Portfolio						
2	0.6182	0.3478	0.5053** (0.0180)	0.4809* (0.0984)	0.4759*** (0.0030)	0.4524 (0.1939)
3	0.3818	0.1304	0.2569*** (0.0072)	0.2405** (0.0601)	0.2214*** (0.0005)	0.205 (0.1986)
4	0.2364	0.0435	0.1351** (0.0111)	0.1132* (0.0574)	0.1097*** (0.0014)	0.0859 (0.2382)
5	0.1333	0	0.0716* (0.0516)	0.0539	0.0528*** (0.0099)	0.0342
6	0.0667		0.0339 (0.1554)	0.0229	0.0225* (0.0503)	0.0107
7	0.0485		0.0148* (0.0808)	0.0089	0.0094** (0.0405)	0.0021
8	0.0303		0.0051* (0.0935)	0.003	0.0033* (0.0728)	0.0009
9	0.0182		0	0	0	0
10	0.0061					
11	0					

Ordered failure time, $t(j)$	Empirical Survival Function		Theoretical Survival Function			
Panel E: Big Size & High book-to-market (**BH**) Portfolio						
2	0.6527	0.36	0.4956*** (0.0008)***	0.4984* (0.0761)	0.4923*** (0.0006)	0.5041* (0.0641)
3	0.4491	0.12	0.256 (0.0000)	0.2457** (0.0217)	0.2563*** (0.0000)	0.2567** (0.0124)
4	0.3293	0.04	0.1266*** (0.0000)	0.1164** (0.0259)	0.1263*** (0.0000)	0.1241** (0.0142)
5	0.2395	0	0.0619*** (0.0000)	0.0519	0.0611*** (0.0000)	0.056
6	0.1557		0.0277*** (0.0001)	0.0211	0.0269*** (0.0001)	0.0237
7	0.1018		0.0109*** (0.0006)	0.0081	0.0098*** (0.0005)	0.0089
8	0.0659		0.0032*** (0.0036)	0.002	0.0024*** (0.0032)	0.0019
9	0.0419		0	0	0	0
10	0.024					
11	0.018					
12	0.012					
13	0.006					
14	0					