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Momentum and market volatility: a Bayesian regime-switching model

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ABSTRACT
Our study finds that momentum is a persistent phenomenon that exhibits great variability in its strength in the UK stock market. Inspired by psychological evidence that cognitive biases can shift overtime, we conjecture that there may be two stock market states, namely, the calm and the turbulent market state, and that the switch between these two market states is governed by market volatility. Using Bayesian estimation methods, our results confirm the role of market volatility as the critical switching variable, which is also found to have additional predictive power for momentum returns in the turbulent market state. Somewhat contradictory to the findings in cross-sectional studies, we find that past returns have a negative impact on momentum profits. We also find that both winners and losers tend to perform better in the turbulent market state than in the calm market state and that losers' outperformance is responsible for large momentum losses in the turbulent market state. Investment strategies that take advantage of the predictability of momentum dynamics outperform momentum strategies. Our findings are not readily reconciled with risk-based explanations but can be loosely explained in a behavioural framework.

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G11; G12

1. Introduction

Momentum, first documented by Jegadeesh and Titman (1993), is a well-established phenomenon in the stock market. In the rational framework, momentum profits reflect variations in expected returns and are compensations for risks (Johnson 2002; Sagi and Seasholes 2007; Vayanos and Woolley 2013; Albuquerque and Miao 2014); whereas in the behavioural framework, momentum profits are the outcome of exploiting mispriced stocks, thanks to cognitive biases or bounded rationality (Barberis, Shleifer, and Vishny 1998; Daniel, Hirshleifer, and Subrahmanyam 1998; Hong and Stein 1999). Despite more than two decades of extensive studies, empirical findings on the sources of momentum profits are mixed and the question 'what drives momentum?' remains.

Recent research work, including Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), and Dobrynskaya (2019), finds that momentum strategies that are profitable on average over time suffer occasional substantial losses and that these losses are predictable to some extent.[1] These empirical findings on momentum dynamics and its predictability are intriguing and offer a new perspective for us to examine the causes of momentum and its time-varying characteristics. Daniel and Moskowitz (2016) conclude that none of the crash risk, volatility risk, and Fama and French (1993) factors, can fully explain their findings. They also point out that the existence of the same phenomena and option-like features for momentum strategies in other financial asset markets challenges explanations such as Merton (1974) story. Dobrynskaya (2019) investigates the explanatory power of 13 risk factors for the profitability of investment strategies based on the predictability of momentum crashes, and all factor betas except one are found to be close to zero and statistically insignificant.

We take a different approach from earlier studies, and we conjecture that there are different price mechanisms at work in different market states defined by market volatility. This conjecture is based on the evidence

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of dynamic allocation of limited attention (e.g. Peng and Xiong 2006), time-varying ambiguity aversion (e.g. Heath and Tversky 1991), and their associations with market volatility. Compared with modest market volatility periods, extremely high market volatility periods feature high market returns accompanied by strong reversals (Schwert 1990) and their occurrence is relatively rare. The rare occurrence of extremely high market volatility can cause shifts in investors' psychology during decision-making process in trading and investing, which in turn results in significant changes in stock price behaviour.

A two-regime switching model is constructed accordingly to capture the role of market volatility in propelling large reversals in momentum. When market volatility is below a threshold, the stock market is in the calm state, whereas when market volatility is above the threshold, the stock market is in the turbulent state. Apart from being the switching variable in this model, market volatility is also a regressor. Wang and Xu (2015) document that market volatility has significant predictive power for momentum returns. Moreover, in unreported results, Barroso and Santa-Clara (2015) find that the realised variance of stock market can replace the realised momentum risk in forecasting future momentum risk.

We also consider past return, more specifically, the return of a momentum portfolio over its ranking period, as another regressor. Rationalists and behaviourists have different interpretations of momentum returns, which implies different expected relationships between a momentum portfolio's return over its ranking period and that over its holding period. From the rationalists' point of view, momentum returns reflect higher (lower) expected returns for winners (losers), hence, a positive relationship is expected.[2] In contrast, behaviouralists believe that momentum could be the outcome of either underreaction or overreaction to news,[3] which suggests an inverse relationship. The higher is the ranking period return, the more dominant is overreaction in the stock market, hence the higher chance of subsequent reversal in momentum.

Our study focuses on the UK stock market, and we find that momentum is a persistent phenomenon with great variation in its strength in the UK stock market based on the performance of 48 momentum strategies during 1969–2019. Consistent with the findings in the US stock market, momentum losses tend to be substantial when the UK stock market is recovering from severe market-wide selloffs.

In a two-regime model, the transition point is critical. Rather than experimenting with arbitrary levels of the threshold volatility as Dobrynskaya (2019) does in defining significant market plunge, we estimate it here by Bayesian methods and the estimation results confirm the role of market volatility as an indicator of switch between the calm market state and the turbulent market state where momentum strategies perform significantly differently. Market volatility is found to have a considerable negative impact on momentum returns in the turbulent market state. A significant negative relationship is also found between the ranking and the holding period return in the calm market state. This negative relationship can lead to momentum losses when the ranking period return is sufficiently large. In other words, the estimation results suggest that momentum can reverse in both market states; however, the reversal in the calm market is associated with extreme past return whereas in turbulent market it is linked to extreme market volatility. The estimation results largely support the conjecture of two regimes for short-term stock price behaviour and our findings point to time-varying cognitive biases as plausible driving forces of momentum dynamics.

Momentum dynamics, especially the occurrence of large reversals, are highly predictable. We show that an investment strategy that switches from momentum to contrarian under the guidance of our two-regime model has superior performance compared to the momentum strategy. It is worth noting that the threshold volatility level that separates the two regimes is estimated alongside the other parameters of our model. Since the parameters of our model are estimated by Bayesian updating, we do not assume that investors know the full-period parameter estimates from the outset, making our approach somewhat closer to the practical realities faced by portfolio managers in the market. The superior performance of the model-guided investment strategy is robust over time and across different ranking and holding periods.

Our work is closely related to Wang and Xu (2015) and Dobrynskaya (2019). Wang and Xu (2015) focus on the impact of market volatility on momentum returns and document significant negative impact of market volatility on momentum returns in the US stock market, which is amplified in down markets. Dobrynskaya (2019) focuses on the timing of momentum crashes and notices that momentum strategies tend to take a big hit in one to three months following a significant market plunge. A dynamic strategy that executes momentum trade in normal times but switches to contrarian trade in one month after a severe market fall generates superior performance as it turns big momentum losses into gains. Her strategy works well in various geographical market including the UK stock market. Our findings echo both studies to some extent regarding the impact of market volatility on momentum returns and the predictability of momentum crashes. However, our study finds that the part that the market return plays in predicting momentum in their studies can be covered by market volatility as market volatility alone is sufficient in indicating market conditions in our two-regime switching model. Similar to the ideas of Dobrynskaya (2019)'s dynamic strategy, our model-guided investment strategy also exploits the predictability of reversals and alternates the use of momentum and contrarian trades; however, our strategy tends to execute contrarian trades after market crashes as well as in an exuberant market.

Our study contributes to the literature in two ways. Firstly, it updates the results concerning the profitability of momentum strategies in the UK stock market based on a great number of momentum strategies. Momentum effect in the US stock market has been intensively studied in the literature, however, research that focuses on the UK stock market, one of the biggest stock markets in the world, is lagging. An update on momentum profitability in the UK stock market is long overdue as it has not been systematically examined since Galariotis, Holmes, and Ma (2007). Our study extends their results to 2019, covering the tumultuous years of the Great Financial Crisis of 2007–2008 and the subsequent recovery. Secondly and more importantly, we employ a new approach, regime-switching, to probe into momentum dynamics and its possible causes. Regime-switching models have been used in many macroeconomic time-series studies, but not yet in momentum studies. The use of a two-regime switching model in our study is fruitful in that it reveals a nonlinear relationship between market volatility and momentum returns and an asymmetric impact of the ranking period return on the hold period return, which help identify drivers of momentum dynamics in different market states.

The remainder of this paper is organised as follows. Section 2 investigates the profitability of momentum strategies and evaluates the characteristics of momentum returns in the UK stock market. Section 3 provides rationales for the construction of a two-regime switching model for momentum dynamics. Section 4 specifies the two-regime switching model and presents the estimation results. This section also tests the model's out-of-sample predictive power and discusses the performance of a new investment strategy that takes advantage of its predictive power. Section 5 carries out robustness checks by applying the two-regime switching model to a range of momentum strategies for different sample periods. We also show that similar mechanisms can be observed in the US stock market. Section 6 discusses the findings and Section 7 concludes.

2. Momentum in the UK stock market

2.1. Data and momentum strategy formation method

Monthly stock return data are from the London Share Price database (LSPD) and the sample consists of all stocks listed on London Stock Exchange (LSE) from Jan 1969 to Sep 2019 except odd foreign mining and banking shares, shares traded on the Unlisted Securities Market (USM), other unlisted securities, Third Market companies, O.T.C. companies, AIM and OFEX companies. Stocks with missing value(s) during the 12 months prior to the portfolio formation are also excluded; however, stocks with missing value(s) during the holding period are included to avoid survivorship bias. The number of eligible stocks in each month ranges from 734 to 1064.

To implement the momentum strategy J × K, we do the following. At the beginning of each month t, all eligible stocks are sorted in descending order into deciles based on their buy-and-hold return over the J-month ranking period, $r^i_{t-J,t-1}\left(=\prod_{j=1}^{J}(1+r^i_{t-j})-1\right)$. Continuously compounded return (CCR) calculated as the first difference in the log of prices, is widely used in the literature. However, as Dissanaike (1994) points out, CCR is not as precise a measure of return as buy-and-hold return. These two different calculations can affect the results of stock selection and hence lead to different constituents of momentum portfolios.

The top (bottom) decile of stocks with equal weight forms the winner (loser) portfolio. To mitigate bid-ask bias and bias induced by nonsynchronous trading, we skip one month between the ranking and the holding period, that is, the momentum strategy J × K is implemented one month after formation. At the beginning of month $t+1$, we purchase the winner portfolio and sell the loser portfolio at the same time to implement the momentum portfolio J × K. The performance of winner (loser) portfolio is measured by the arithmetic mean of the top (bottom) deciles of I stocks' buy-and-hold returns over the subsequent K-month holding period, $\frac{1}{I}\sum_{i=1}^{I}(\prod_{k=1}^{K}(1+r_{t+K}^{i})-1)$. The performance of the momentum portfolio J × K implemented in month $t+1$ is measured by the holding period return (hereafter HPR), $r_{t+1,t+K}^{P}$, which is the difference in the K-month buy-and-hold return between the winner and the loser portfolio. The same procedure repeats every month from Jan 1970 to August 2018 to generate the monthly $r_{t+1,t+K}^{P}$ time series data for the momentum strategy J × K.

We follow Arnold and Baker (2007) to remedy the problem of delisting during the holding period. A share is regarded as losing all value in the delisting month if its death type is described in the LSPD as liquidity, quotations cancelled for reasons unknown, received appointed/liquidation, in administration/administrative receivership, or cancelled assumed valueless. For a firm with the other death types (e.g. acquisition, merger, suspension, etc.) during the holding period, proceeds received will be reinvested equally in the other shares in its portfolio and will rebalance monthly afterwards.

In this study, J varies from 3 to 12 at a 3-month interval and K from 1 to 12 at a 1-month interval. In total, 48 momentum strategies are carried out and for each momentum strategy, there are 584 HPR observations. Since the monthly HPR time series data are overlapping, they are highly likely to be autocorrelated. To remedy this issue, the Newey and West (1987, 1994) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator is employed to estimate the variance with the number of lags set at 12.

2.2. Profitability of momentum strategies

Table 1 reports the average HPRs and the annualised average HPRs of all 48 momentum strategies over the whole sample period. The annualised average HPR is calculated using the conversion formula $((1+r_{t+1,t+K}^{P})^{1/k}-1)*12$. It is striking to see that all 48 momentum strategies generate profits and 46 of them are profitable at the significance level of 5%. 17 momentum strategies achieve annual HPRs that are above 10%. It is also worth noting that the average HPR starts to decline toward the end of the 12-month holding period, which indicates that momentum is a short-term effect.[4]

We also examine the performance consistency of momentum strategies over time, by splitting the whole sample period into four sub-sample periods: Jan 1969–Dec1981, Jan 1982–Dec 1997, Jan 1998–Dec 2010, and Jan 2011–Sep 2019. The first sub-sample period includes the 1973–1974 stock market crash and the second sub-sample period covers the 1987 crash. The sub-sample period Jan 1998–Dec 2010 includes a number of major downturns including the burst of the tech bubble in 2000 and the Lehman crisis of 2008. By contrast, the UK stock market was largely free of big shocks during the final sub-sample period.

Table 1. Profitability of momentum strategies in the UK stock market (Jan 1969–Sep 2019).

J × K		1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
3M	Avg. HPR	0.40	1.44	2.40	3.21	3.97	4.57	5.14	5.84	6.87	7.56	8.03	7.85
	Ann. HPR	4.76	8.61	9.53	9.51	9.38	8.98	8.62	8.54	8.89	8.78	8.45	7.58
	t-stat	*(1.86)*	*(3.79)*	*(4.17)*	*(3.97)*	*(3.95)*	*(3.84)*	*(3.86)*	*(3.99)*	*(4.39)*	*(4.52)*	*(4.52)*	*(4.15)*
6M	Avg. HPR	0.59	1.88	3.08	3.97	4.88	5.99	6.84	7.66	8.11	8.25	8.12	7.71
	Ann. HPR	7.09	11.26	12.18	11.75	11.49	11.69	11.39	11.12	10.44	9.55	8.55	7.45
	t-stat	*(1.93)*	*(3.40)*	*(3.77)*	*(3.60)*	*(3.49)*	*(3.66)*	*(3.75)*	*(3.85)*	*(3.78)*	*(3.63)*	*(3.38)*	*(3.04)*
9M	Avg. HPR	0.58	1.80	3.22	4.30	5.28	5.95	6.41	6.76	6.79	6.76	6.71	6.32
	Ann. HPR	7.00	10.75	12.75	12.70	12.42	11.61	10.71	9.85	8.79	7.88	7.10	6.14
	t-stat	*(1.83)*	*(2.95)*	*(3.62)*	*(3.56)*	*(3.48)*	*(3.27)*	*(3.12)*	*(3.01)*	*(2.79)*	*(2.59)*	*(2.43)*	*(2.18)*
12M	Avg. HPR	0.76	1.90	2.88	3.54	4.12	4.44	4.73	4.86	4.84	4.58	4.27	3.95
	Ann. HPR	9.08	11.34	11.41	10.49	9.73	8.72	7.95	7.14	6.32	5.38	4.57	3.88
	t-stat	*(2.39)*	*(3.07)*	*(3.08)*	*(2.81)*	*(2.60)*	*(2.36)*	*(2.23)*	*(2.09)*	*(1.93)*	*(1.72)*	*(1.52)*	*(1.35)*

Note: This table reports the average HPRs (in %), the annualised average HPRs (in %) and Newey and West (1987, 1994) adjusted t-statistics for the 48 momentum strategies. The annualised average HPR is calculated using the conversion formula $((1+r_{t+1,t+K}^{P})^{1/k}-1)*12$. The momentum strategy J × K is carried out every month from Jan 1970 to Aug 2018. In total, there are 584 HPR observations for each strategy.

Table 2. Profitability of momentum strategies for sub-sample periods.

J × K		1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
1969–1981													
3M	Ann. HPR	–	–	–	–	–	–	5.03	5.48	6.67	7.32	7.49	6.70
	t-stat	–	–	–	–	–	–	*(1.77)*	*(2.05)*	*(2.71)*	*(2.97)*	*(2.98)*	*(2.65)*
6M	Ann. HPR	–	–	–	–	–	7.41	7.87	8.34	8.34	7.99	7.61	7.06
	t-stat	–	–	–	–	–	*(2.04)*	*(2.28)*	*(2.53)*	*(2.58)*	*(2.53)*	*(2.41)*	*(2.17)*
9M	Ann. HPR	–	–	–	8.18	9.15	9.54	9.24	9.23	8.82	8.52	7.83	7.01
	t-stat	–	–	–	*(1.79)*	*(2.21)*	*(2.44)*	*(2.48)*	*(2.56)*	*(2.53)*	*(2.45)*	*(2.22)*	*(2.00)*
12M	Ann. HPR	–	–	7.87	7.78	8.11	7.92	7.80	7.47	6.93	6.26	–	–
	t-stat	–	–	*(1.69)*	*(1.76)*	*(1.95)*	*(1.99)*	*(2.03)*	*(2.01)*	*(1.93)*	*(1.77)*	–	–
1982–1997													
3M	Ann. HPR	8.21	11.61	12.52	12.63	12.63	12.49	12.31	12.07	11.99	11.43	10.93	10.26
	t-stat	*(2.62)*	*(4.41)*	*(4.76)*	*(4.50)*	*(4.52)*	*(4.52)*	*(4.77)*	*(5.02)*	*(5.33)*	*(5.08)*	*(5.03)*	*(4.86)*
6M	Ann. HPR	11.01	14.58	16.75	16.46	16.78	16.89	16.31	15.83	14.83	13.66	12.00	10.45
	t-stat	*(3.04)*	*(4.28)*	*(4.93)*	*(4.72)*	*(4.90)*	*(5.17)*	*(5.18)*	*(5.21)*	*(5.10)*	*(4.66)*	*(3.89)*	*(3.33)*
9M	Ann. HPR	11.70	15.17	17.43	17.89	17.79	16.92	15.90	14.45	12.66	10.95	9.53	8.09
	t-stat	*(2.91)*	*(3.99)*	*(4.52)*	*(4.56)*	*(4.58)*	*(4.43)*	*(4.25)*	*(3.85)*	*(3.32)*	*(2.79)*	*(2.39)*	*(2.01)*
12M	Ann. HPR	14.21	16.67	17.03	16.29	15.38	13.79	12.70	11.41	9.96	8.38	7.08	–
	t-stat	*(3.41)*	*(3.96)*	*(3.99)*	*(3.69)*	*(3.46)*	*(3.10)*	*(2.93)*	*(2.68)*	*(2.39)*	*(2.05)*	*(1.77)*	–
1998–2010													
3M	Ann. HPR	–	10.86	–	–	–	–	–	–	–	–	–	–
	t-stat	–	*(1.82)*	–	–	–	–	–	–	–	–	–	–
6M	Ann. HPR	–	–	–	–	–	–	–	–	–	–	–	–
	t-stat	–	–	–	–	–	–	–	–	–	–	–	–
9M	Ann. HPR	–	–	–	–	–	–	–	–	–	–	–	–
	t-stat	–	–	–	–	–	–	–	–	–	–	–	–
12M	Ann. HPR	–	–	–	–	–	–	–	–	–	–	–	–
	t-stat	–	–	–	–	–	–	–	–	–	–	–	–
2011–2019													
3M	Ann. HPR	9.87	9.95	10.21	10.91	11.13	10.97	11.15	11.58	11.63	10.81	9.90	8.81
	t-stat	*(2.83)*	*(3.39)*	*(3.90)*	*(4.46)*	*(4.70)*	*(4.62)*	*(4.73)*	*(4.70)*	*(4.46)*	*(3.80)*	*(3.25)*	*(2.83)*
6M	Ann. HPR	15.55	17.65	17.60	17.58	16.84	16.88	16.23	15.35	14.34	12.88	11.76	10.52
	t-stat	*(3.60)*	*(4.53)*	*(4.97)*	*(5.55)*	*(4.96)*	*(4.68)*	*(4.23)*	*(3.86)*	*(3.50)*	*(3.13)*	*(2.91)*	*(2.65)*
9M	Ann. HPR	16.89	18.41	18.44	18.46	17.65	16.95	15.64	14.63	13.53	12.52	11.58	10.37
	t-stat	*(3.20)*	*(3.81)*	*(3.88)*	*(3.93)*	*(3.58)*	*(3.32)*	*(3.04)*	*(2.93)*	*(2.76)*	*(2.65)*	*(2.61)*	*(2.43)*
12M	Ann. HPR	17.16	18.41	17.33	16.14	14.81	14.09	13.03	12.05	11.07	9.99	8.95	7.77
	t-stat	*(2.71)*	*(3.34)*	*(3.23)*	*(3.07)*	*(2.91)*	*(2.85)*	*(2.69)*	*(2.53)*	*(2.38)*	*(2.26)*	*(2.11)*	*(1.88)*

Note: The whole sample period Jan 1969–Sep 2019 is divided into four sub-sample periods, Jan 1969–Dec 1981, Jan 1982–Dec 1997, Jan 1998–Dec 2010, and Jan 2011–Dec 2019. This table reports the annualised average HPRs (in %) and Newey and West (1987, 1994) adjusted *t*-statistics for momentum strategies that are profitable at the significance level of 5% for the four sub-sample periods.

Table 2 reports the annualised average HPRs for momentum strategies that generate profits at the significance level of 5% for each sub-sample period and it reveals great variability in profitability over time, indicated by changes in the number of profitable momentum strategies and in the size of annualised average HPRs moving from one sub-sample period to the next. 30 out of the 48 momentum strategies are profitable during Jan 1969–Dec1981, and the number increases to 47 during Jan 1982–Dec 1997. It is remarkable to see the number of profitable momentum strategies plummet to 1 during Jan 1998–Dec 2010. It is even more extraordinary that all 48 momentum strategies turn profitable during Jan 2011–Sep 2019.

The size of the annualised average HPR also displays great variation over time. For example, none of the 48 momentum strategies produce an annualised average HPR above 10% during Jan 1969–Dec 1981 and the maximum annualised average HPR is 9.54% during this sub-sample period, which is generated by the momentum strategy 9 × 6; in contrast, during Jan 1982–Dec1997, 41 momentum strategies achieve better than 10% annualised average HPR and the maximum annualised average HPR reaches 17.89% by the momentum strategy 9 × 4. The size of the annualised average HPR drops sharply as we move to Jan 1998–Dec 2010, which only sees the maximum annualised average HPR at 10.86%. The last sub-sample period experiences the strongest momentum effect as 41 momentum strategies achieve annualised average HPRs greater than 10% and 4 momentum strategies achieve annualised average HPRs above 18%, which are the highest among all sub-sample periods.

These results suggest that momentum is a persistent phenomenon in the UK stock market, however, it varies in its strength over time. The observation of momentum effect being strongest during Jan 2011–Sep 2019 when the stock market is largely free of big crashes and weakest during Jan 1998–Dec 2010 when the stock market experiences two of the biggest stock market crises indicates a possible association between momentum returns and the state of the market.

2.3. Characteristics of momentum returns

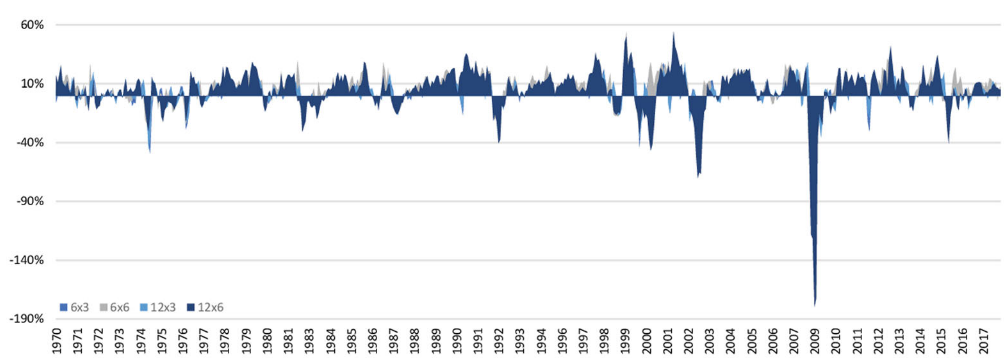
We further investigate the time variation in momentum returns by examining momentum return time series and their relationship with conventional risk factors and variables that are found to have predictive power in prior studies. Results for strategies 6×3, 6×6, 12×3 and 12×6 are reported and they are representative of the results for the other strategies.[5]

Figure 1 is an area chart that plots the monthly HPR time series, and it shows that momentum is present in the UK stock market most of the time. Nevertheless, during the whole sample period, there are 80 out of 584 months, for which, all of these four momentum strategies generate losses. These results suggest that the momentum effect is absent occasionally and replaced by the contrarian effect in the short run in the UK stock market. In line with the findings by Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016), and Dobrynskaya (2019) in the US stock market, momentum strategies suffer substantial losses when the stock market recovers from crashes. Indeed, the biggest losses that momentum strategies generate during the entire sample period happen when the market rebounds from the Dot-Com Crash of 2000–2002 and the Stock Market Crash of 2008.

The distributional characteristics of momentum returns including the range, skewness, and kurtosis are presented in Table 3 Panel A. Consistent with the literature, momentum returns are negatively skewed with large kurtosis values. For example, the momentum strategy 6×3 has the maximum HPR at 30.84% and the minimum HPR at -109.13%. Its HPR has skewness of -3.49 and kurtosis of 26.3.

Table 3 Panel B reports the estimation results of both CAPM and Fama–French 3-factor model[6] and they confirm the findings of prior studies that momentum returns are not attributable to exposure to common risk factors. In fact, momentum returns are higher after adjusting for market risk since the point estimates of beta are negative though not significantly different from zero. The anomaly is even more noticeable after adjusting for the Fama–French common risk factors, as the loadings on all risk factors are negative.

We also run a regression to test the predictive power of market return and market volatility as Wang and Xu (2015) document that they are significant explanatory variables for momentum profits in the US stock market.



This area chart plots monthly HPR time series of momentum strategies 6x3, 6x6, 12x3 and 12x6 over the whole sample period Jan 1969-Sep 2019.

Figure 1. Momentum dynamics.

Table 3. Summary statistics for momentum returns.

	6 × 3	6 × 6	12 × 3	12 × 6
Panel A. Distributional characteristics of momentum returns				
Max (in %)	30.84	53.94	33.19	54.14
Min (in %)	−109.13	−174.30	−106.21	−179.63
Skewness	−3.49	−4.58	−2.88	−3.80
Kurtosis	26.30	38.13	19.19	28.14
Panel B. Estimation results of CAPM and FF3F model				
CAPM Alpha (in %)	3.20	8.39	4.41	6.35
	(5.24)	*(5.91)*	*(3.63)*	*(3.35)*
CAPM Beta	−0.31	−0.46	−0.27	−0.49
	(−1.68)	*(−1.58)*	*(−1.35)*	*(−1.61)*
Adj-R^2	*0.032*	*0.056*	*0.021*	*0.052*
3-Factor Alpha (in %)	3.83	9.63	4.74	8.52
	(6.38)	*(6.21)*	*(5.08)*	*(4.47)*
SMB	−0.55	−0.53	−0.64	−0.60
	(−1.79)	*(−1.36)*	*(−2.10)*	*(−1.52)*
HML	−0.58	−0.49	−0.87	−0.88
	(−3.00)	*(−2.42)*	*(−6.81)*	*(−6.14)*
RM-RF	−0.20	−0.32	−0.16	−0.34
	(−1.53)	*(−1.53)*	*(−1.10)*	*(−1.58)*
Adj-R^2	*0.193*	*0.174*	*0.280*	*0.279*
Panel C. Estimation results of the regression model $r^P_{t+1,t+K} = \alpha + \beta_1 mr_{t-12,t-1} + \beta_2 vol_{t-J,t-1} + \beta_3 vol_{t-J,t-1} * dummymr_{t-12,t-1}$				
Intercept (in %)	11.56	23.53	12.76	23.95
	(3.61)	*(3.54)*	*(4.69)*	*(4.63)*
12-Month Lagged Market Return	−0.02	−0.09	−0.01	−0.07
	(−0.62)	*(−1.61)*	*(−0.23)*	*(−0.86)*
Ranking Period Market Volatility	−0.70	−1.40	−0.60	−1.14
	(−2.41)	*(−2.32)*	*(−3.17)*	*(−2.98)*
Ranking Period Market Volatility∗ 12-Month Lagged Market Return Dummy	−0.27	−0.58	−0.13	−0.34
	(−1.54)	*(−1.81)*	*(−0.96)*	*(−1.43)*
Adj-R^2	*0.142*	*0.225*	*0.119*	*0.175*

Note: Panel A presents characteristics of the momentum returns during Jan 1969–Sep 2019 including range, skewness, and kurtosis for HPRs. Panel B reports the estimation results of the CAPM and the Fama–French 3-factor model based on data from Oct 1980 to Dec 2017. Panel C reports the estimation results regarding the predictive power of lagged market return and lagged market volatility based on data from Jan 1969 to Sep 2019. Newey and West (1987, 1994) adjusted *t*-statistics are displayed in parentheses.

More specifically, Wang and Xu (2015) find that macroeconomic variables, including dividend yield, yield spread between Baa-rated bonds and Aaa-rated bonds, yield spread between ten-year Treasury bonds and three-month Treasury bills, and yield on a T-bill with three months to maturity, do not have incremental predictive power after controlling for the market return and market volatility.

The HPR, $r^P_{t+1,t+K}$, is regressed on the 12-month lagged market return, $mr_{t-12,t-1}$, ranking period market volatility, $vol_{t-J,t-1}$, and ranking period market volatility∗12-month lagged market return dummy variable, $vol_{t-J,t-1} * dummymr_{t-12,t-1}$. The dummy variable takes the value of 0 if the 12-month lagged market return is positive and 1 otherwise. The FTSE All-Share index is used as the proxy of the UK stock market.[7] The regression results are reported in Table 3 Panel C and they confirm the significance of market volatility in predicting momentum returns. Although it seems that the market volatility has a greater negative impact on momentum returns in the down market, the incremental impact is much smaller than that documented by Wang and Xu (2015) in the US stock market, and it is not universally significant across momentum strategies. In addition, there lacks strong evidence for the significant predictive power of lagged market return as a continuous variable.

3. Construction of two-regime switching model for momentum dynamics

The results in Section 2 confirm that there is a significant association between momentum and lagged market volatility in the UK stock market and add to the evidence that market volatility has significant predictive power for momentum dynamics;[8] nevertheless, there is no satisfactory explanation yet for the association between market volatility and momentum dynamics. Although Barroso and Santa-Clara (2015) find that the realised variance of the market produces estimates of momentum risk as good as momentum's own lagged risk, they did not explore possible explanations. Wang and Xu (2015) find that default risk is intimately linked to volatile down markets; however, they also point out that default risk alone does not account for all their findings and that the default risk-based explanation contradicts cross-sectional results.

In this study, we conjecture that there are two market states defined by the level of market volatility and that market participants behave differently between the two market states. In the following, we argue for the role of market volatility in driving significant changes in investors' behaviour and provide rationales for the ranking period return (hereafter RPR) as an explanatory variable for momentum returns.

3.1. Role of market volatility in defining stock market states

Rational asset pricing models typically assume instantaneous reaction to news by investors upon its arrival. This assumption requires investors to be always able to allocate sufficient attention to all new information. However, attention is a scarce cognitive resource (Kahneman 1973) and investors are facing this cognitive capacity constraint in the process of making investment decisions. Asset prices can only respond to news that investors have paid attention to (Huberman and Regev 2001). Peng and Xiong (2006) model the attention-constrained investors' learning process and they show that the 'optimal' attention allocation to market-, sector-, and firm-specific information is a dynamic process which depends on the extent of the uncertainty in the three types of information. In severely constrained cases, investors allocate all attention to market and sector information and ignore all the firm-specific data. Empirical research shows that extreme market volatility is one of such severely constrained cases. For example, Peng, Xiong, and Bollerslev (2007) document contemporaneous increase in the market volatility and the movement of individual stocks with the arrival of market-wide macroeconomic shocks. Dimpfl and Jank (2016) find a strong co-movement of stock market indices' realised volatility and the search queries for their names. Shift in attention allocation can cause investors to change their trading behaviours and strategies. For example, Yuan (2015) discovers that high market-wide attention events lead investors to sell in a dramatic fashion when the level of the stock market is high.

Another cognitive factor that tends to change along with market volatility is investors' attitude towards risk. Economists are familiar with ambiguity aversion; however, they are much less aware of time-varying ambiguity aversion, which is potentially very relevant to finance (Barberis 2013). Heath and Tversky (1991) demonstrate that an investor can be either ambiguity-averse or ambiguity-seeking, depending on how competent she feels at analysing the situation at hand. Empirical evidence shows that prior trading outcomes as well as personal familiarity with events can affect investors' confidence (Moore and Healy 2008; Merkle 2017). Since extremely high market volatility occurs rarely, investors have much less or no experience of such market environment, which can lead to self-perception of incompetence in a volatile market. In a nutshell, investors can be ambiguity-seeking in modest market-volatility environment and ambiguity-averse in extremely high market volatility environment.

It follows naturally that stocks could be mispriced due to different irrational behaviours in different market environments defined by the degree of market uncertainty, which in turn results in different subsequent price correction paths. For example, the mispricing could be driven by ambiguity-seeking behaviour and allocation of limited attention to sector- and firm-specific news when market volatility is relatively low and by ambiguity-averse behaviour and allocation of limited attention to economic news when market volatility is extremely high.

In summary, there are good reasons to expect stock market behaviour to be very different in high-volatility market state versus in low-volatility market state.

3.2. Predictive power of ranking period return for momentum return

The RPR should be correlated to the HPR in both the rational and the behavioural paradigm, however, in different ways. In the rational framework, momentum reflects higher (lower) risk and higher (lower) expected returns for winners (losers) and hence it predicts a positive relationship; whereas in the behavioural framework, momentum can be the outcome of either underreaction or overreaction to news, which implies a negative relationship between the RPR and the HPR.

Grundy and Martin (2001) argue that stocks with higher/lower loadings on the stock-specific factors that performed relatively well during the ranking period are more likely to enter the winner/loser portfolio, and that the sign and the size of the strategy's investment period factor loadings reflect the sign and size of the factor realisations during the prior ranking period. It follows that momentum returns are at least partially due to momentum in the stock-specific component of returns. Johnson (2002) proposes a rational framework where stock prices depend on growth rates in a highly sensitive, nonlinear way which implies a positive (negative) change in a firm's growth rate raises (lowers) its growth rate risk. Other things equal, a momentum portfolio is most likely to have long position in firms that have had positive growth rate shocks and short position in those that have had negative growth shocks. Following Johnson (2002), Sagi and Seasholes (2007) build a model of firm's revenues, costs, growth options and show that variation in these attributes lead to cross-sectional momentum. In a nutshell, these rational models imply that winners (losers) continue to be winners (losers), because winners (losers) are of higher (lower) risk. In this view, momentum profits are the realisation of higher (lower) expected returns of stocks of higher (lower) risk level.

In contrast, many authors look for explanations in investor behaviour patterns. Daniel, Hirshleifer, and Subrahmanyam (1998) assume that investors are overconfident about their private information, which leads to overreacting to private information signals and underreacting to public information signals. They show that overconfidence implies negative long-lag autocorrelations and biased self-attribution adds positive short-lag autocorrelations. Based on their model, Daniel, Hirshleifer, and Subrahmanyam (1998) argue that short-run positive return autocorrelations can be caused by under-reaction as well as continuing overreaction which results in long-run correction, the contrarian effect. Hong and Stein (1999) build a behavioural model that features two types of agents, 'news watchers' and 'momentum traders'. Both types of agents are assumed to be boundedly rational in the sense that each of them is only able to process some subset of the available public information. More specifically, the news watchers rely exclusively on their private information; momentum traders rely exclusively on the information in past price changes. The additional assumption is that private information diffuses only gradually through the marketplace, which, as Hong and Stein (1999) show, leads to an initial underreaction of news watchers to news. The underreaction leaves opportunities for further future profits that momentum traders will arbitrage away. Hong and Stein (1999) go on to show that momentum traders' arbitrage does not lead to market efficiency and instead the fact that momentum traders only rely on price history leads to an eventual overreaction to any news. A negative relationship is expected between the RPR and the HPR from the behavioural point of view. It follows the logic that the higher the RPR, the more likely the occurrence of overreaction during the ranking period, hence, the more likely the occurrence of reversal during the holding period.

In the following section, we start by constructing a two-regime model and describing the time-varying characteristics of these two proposed regressors. We show that this model can help to explain the observed outcome of pursuing momentum strategies in the UK stock market, in particular, the occasional large losses. We go on to demonstrate that this model has significant predictive power and that an investment strategy guided by the model would outperform a momentum strategy consistently, giving a superior return with lower risk.

4. A two-regime switching model with heteroskedasticity

4.1. Model specification

Based on the discussion in Section 3, we build a two-regime switching model with heteroskedasticity. In this model, a momentum portfolio's HPR is the dependent variable, and the ranking period market volatility (hereafter RPMV) is the switching variable. The momentum portfolio's RPR is a regressor. The RPMV is another regressor as Wang and Xu (2015) document that lagged market volatility has significant predictive power for momentum returns and that business cycle variables do not have incremental predictive power after controlling for lagged market volatility and market state in terms of the lagged market return. Thus, apart from being an indicator of switching, the RPMV may still have explanatory power. The lagged market return is not considered as it is found to have no significant predictive power for momentum as a continuous variable in Section 2.3. Both regimes share the same independent variables, and the two-regime switching model with heteroskedasticity is specified as below.

$$r^P_{t+1,t+K} = [1 - I_{[\tau,\infty)}(vol_{\mathrm{t-J,t-1}})](\alpha_1 + \beta_1 vol_{\mathrm{t-J,t-1}} + \gamma_1 r^P_{\mathrm{t-J,t-1}}) + I_{[\tau,\infty)}(vol_{\mathrm{t-J,t-1}})(\alpha_2 + \beta_2 vol_{\mathrm{t-J,t-1}} + \gamma_2 r^P_{t-J,t-1}) + \varepsilon_t \quad (1)$$

$$Var(\varepsilon_t) = \sigma_1^2[1 - I_{[\tau,\infty)}(vol_{\mathrm{t-J,t-1}})] + \phi\sigma_1^2 I_{[\tau,\infty)}(vol_{\mathrm{t-J,t-1}}) \quad (2)$$

$I_{[\tau,\infty)}(vol_{\mathrm{t-J,t-1}})$ is an indicator function with τ as the threshold parameter. $I_{[\tau,\infty)}(vol_{\mathrm{t-J,t-1}})$ equals 1 if $vol_{\mathrm{t-J,t-1}} \in [\tau,\infty)$ and 0 otherwise. When $vol_{\mathrm{t-J,t-1}}$ is below τ, the market is in the calm market state, whereas when $vol_{\mathrm{t-J,t-1}}$ is above τ, it is in the turbulent market state. Assuming the daily market return is independently and identically distributed, market variance during month t, μ_t^2, is calculated as the variance of the daily market returns during the month multiplied by 20, the number of trading days during a one-month period. Market volatility over the J-month ranking period, $vol_{\mathrm{t-J,t-1}}$, is estimated as $\left(\sum_{j=1}^{J} \mu_{t-j}^2\right)^{1/2}$. σ_1^2 and σ_2^2 denotes the variance of the error term in the calm market state and in the turbulent market state, respectively. $\phi = \sigma_2^2/\sigma_1^2$. The RPR, $r^P_{t-J,t-1}$, and the RPMV, $vol_{\mathrm{t-J,t-1}}$, are the independent variables in both regimes. A constant term is also included in both regimes to capture the amount of momentum return that cannot be explained by the regressors. Model estimation and discussion in this section are based on the momentum strategy 12 × 6. To avoid being repetitive, the momentum strategy 12 × 6 is referred to as the momentum strategy in the remainder of Section 4.

4.2. Characteristics of independent variables

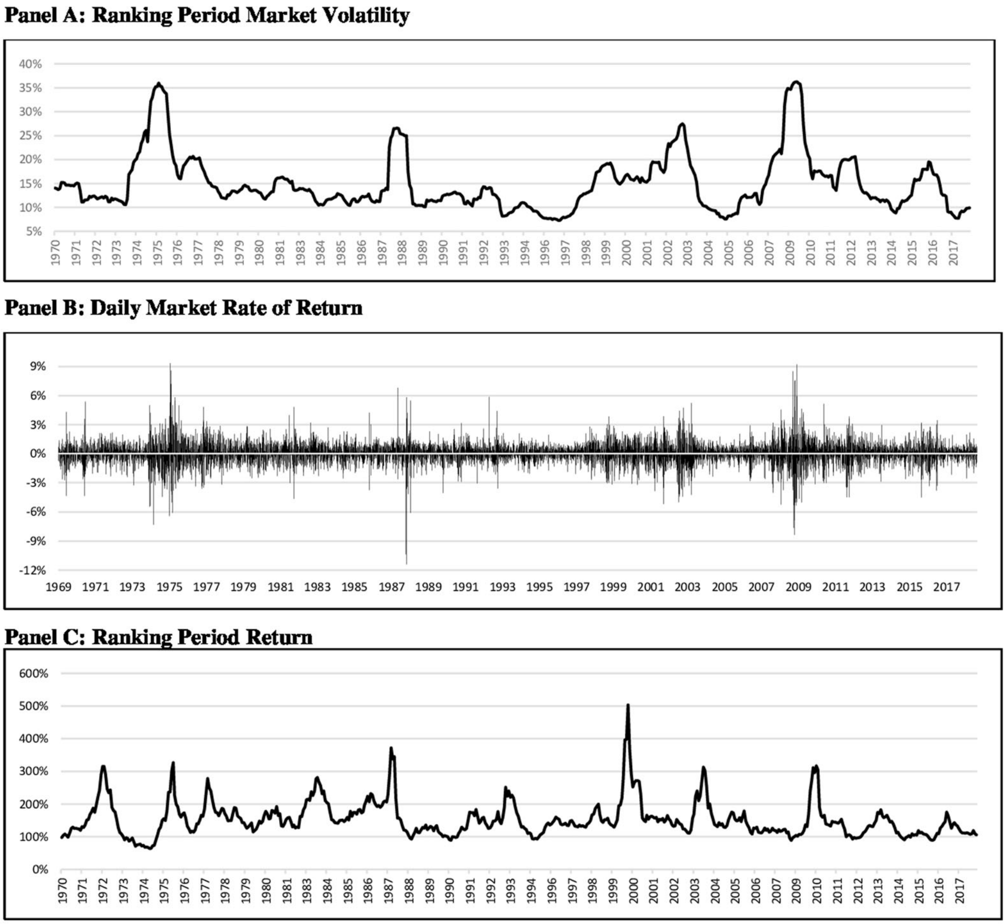
Before the model estimation, we explore the characteristics of the independent variables. Figure 2 plots the 12-month RPMV in Panel A, the daily market return in Panel B, and the 12-month RPR time series in Panel C.

A prominent feature revealed about the 12-month RPMV is the occasional episodes of skyrocketing and subsequently receding movement. It can be seen that extremely high market volatility is accompanied by extremely large daily market returns with alternating signs. These observations in the UK stock market echo those in the US stock market documented by Schwert (1990) and provide evidence that episodes of extreme market volatility are rare. Panel C depicts the RPR time series, and the marked feature is the recurring spikes. The magnitude of these spikes is remarkable. For instance, the 12-month RPR from Feb 1999 to Jan 2000 reaches a staggering 503%. The 12-month RPR has an average of 154% and skewness of 1.82 over the whole sample period. Based on the sample data, the 12-month RPMV and the 12-month RPR are weakly negatively correlated with correlation coefficient of −0.038.

4.3. Model estimation results

Bayesian methods are employed to estimate the model in Section 4.1 (see Appendix 1 for the posterior distributions). Koop and Potter (1999) make arguments for the superiority of Bayesian methods when evaluating evidence of nonlinearity in economic time series in general. Moreover, according to Lubrano (1998), in estimating a regime-switching model, there is less need to strictly separate the step- and the smooth-transition models in a Bayesian framework than in a classical framework since the posterior distribution of the threshold parameter τ gives direct evidence regarding the smoothness of switching. For example, if the majority of the probability is concentrated around a single value, this is confirmation of an abrupt switch, whereas if the posterior distribution of τ is more dispersed, it is an indication of a gradual transition.

It can be difficult to choose the 'right' priors in Bayesian estimation and arguably both informative and non-informative priors have their pros and cons. In this study, we opt for non-informative priors for τ and ϕ following



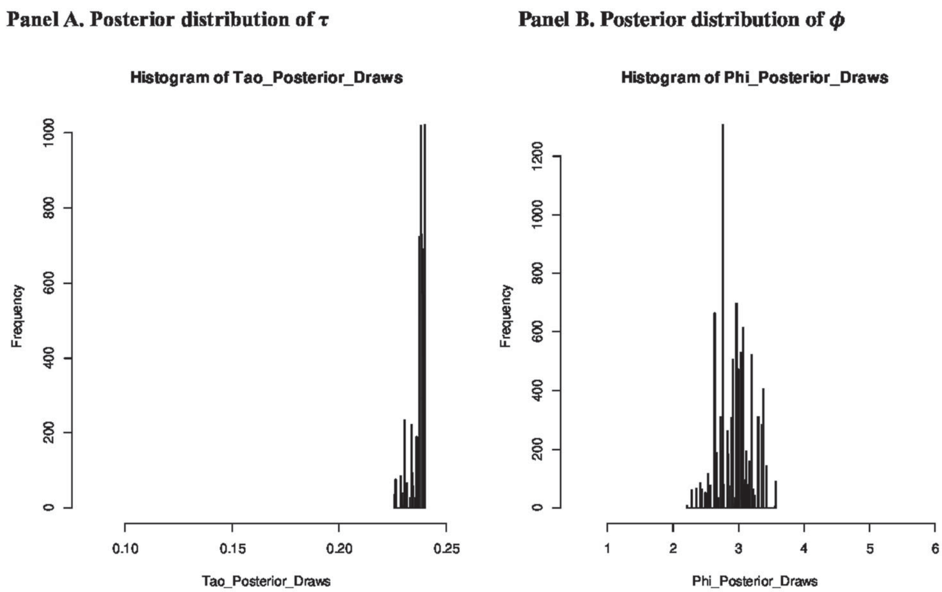
Panel A plots the 12-month market volatility, Panel B the daily rate of return on FTSE All index, and Panel C the 12-month RPR, over the whole sample period Jan 1969-Sep 2019.

Figure 2. Time variation in 12-month ranking period market volatility, daily market rate of return, and 12-month ranking period return.

the principle of indifference since we have no prior knowledge about them. Moreover, to have a reasonably good level of statistical power for both regimes, we choose a support for the prior distribution of τ so that there are no less than 25 observations in each regime. More specifically, a uniform distribution with support (0.08, 0.28) is assigned to τ as the prior distribution and a uniform distribution with distribution support (0.5, 6.0) is chosen as the prior distribution of ϕ. Figure 3 plots the posterior distributions of τ and ϕ.[9]

Panel A shows the posterior distribution of τ. Clearly, the posterior distribution of τ is not bell-shaped, rather, it clusters within a narrow range of (0.22, 0.24), which implies that the switch between the calm and the turbulent market state is abrupt. Panel B presents the posterior distribution of ϕ. The fact that the entire posterior distribution of ϕ lies above 2 confirms that the variance of the error term in the turbulent market state is significantly larger than that in the calm market state, which supports the existence of heteroscedasticity in the variance of the error term.

According to the estimation result of τ, there are 522 observations in the calm market state ($vol_{t-12,t-1} < 0.22$) and 50 in the turbulent market state ($vol_{t-12,t-1} > 0.24$) over the whole sample period. 12 observations occur when $vol_{t-12,t-1}$ is in the range of (0.22,0.24). We compare the momentum returns between the two regimes and we find that the momentum portfolio is likely to generate losses in the turbulent market state, which tend to be of large scale. In this market state, the HPR has an average of -23.5% and ranges between -179.6% and



Panel A plots the posterior distribution of τ and Panel B plots that of ϕ for the sample period 1969-2019. A uniform distribution with distribution support between 0.08 and 0.28 is assigned to τ as the prior probability distribution. A uniform distribution with distribution support between 0.5 and 6 is assigned to τ as the prior distribution. The posterior distributions of τ and ϕ are both generated by the independent Metropolis–Hastings algorithm with uniform candidate density.

Figure 3. Posterior distributions of τ and ϕ.

10.7%. 68% of the 50 HPRs, that is 34 HPR observations, are negative. By contrast, in the calm market state, the same momentum portfolio performs significantly better. It generates positive returns for 77% of the time, which is more than double the figure in the turbulent market state and has an average HRP of 7.39%. The range of the HPR in the calm market state is (−46.8%, 54.1%), which is narrower than in the turbulent market state.

Further examination reveals that it is the loser portfolio's contrasting behaviour between the two market states that is responsible for the reversal in momentum when market volatility shoots above the threshold over the ranking period. The loser portfolio generates an average HPR of 42.5% with the highest HPR at 202.7% in the turbulent market state compared with that of 4.3% with the highest HPR at 88.6% in the calm market state. Moreover, the loser portfolio produces positive returns for 46 out of the 50 observations, that is 92% of the time in the turbulent market state, compared with 59% in the calm market state. Interestingly, the winner portfolio also performs better, although to a lesser degree, in the turbulent market state than in the calm market state. It generates an average HPR of 19% in the turbulent market state, higher than that of 11.7% in the calm market state. In addition, the winner portfolio is more likely to generate positive returns (92% of the time) in the turbulent market state than in the calm market state (73% of the time).

α_1, β_1, and γ_1 are parameters associated with the calm market state and their posterior distributions are shown in Figure 4 Panel A. α_1 is significantly positive with the 95% credibility interval of (0.213, 0.326). In fact, its entire posterior distribution lies above 0. β_1 measures the impact of the RPMV, $vol_{\mathrm{t}-12,\mathrm{t}-1}$, on the HPR, $r^P_{t+1,t+6}$, and its 95% credibility interval is (−0.736, −0.068), which suggests that the RPMV has significant negative impact on the HPR in the calm market state. It is worth noting that the RPMV alone is unlikely to reverse the momentum effect as it can only take values below 0.25. γ_1 reflects the relationship between the RPR, $r^P_{\mathrm{t}-12,\mathrm{t}-1}$, and the HPR, $r^P_{t+1,t+6}$. The fact that its entire posterior distribution lies below 0 with the 95% credibility interval of (−0.114, −0.071) indicates a significant negative relationship between the RPR and the HPR. These estimation results suggest that in the calm market state, the momentum strategy should generate profits as long as the RPR is small and losses if the RPR becomes sufficiently large.

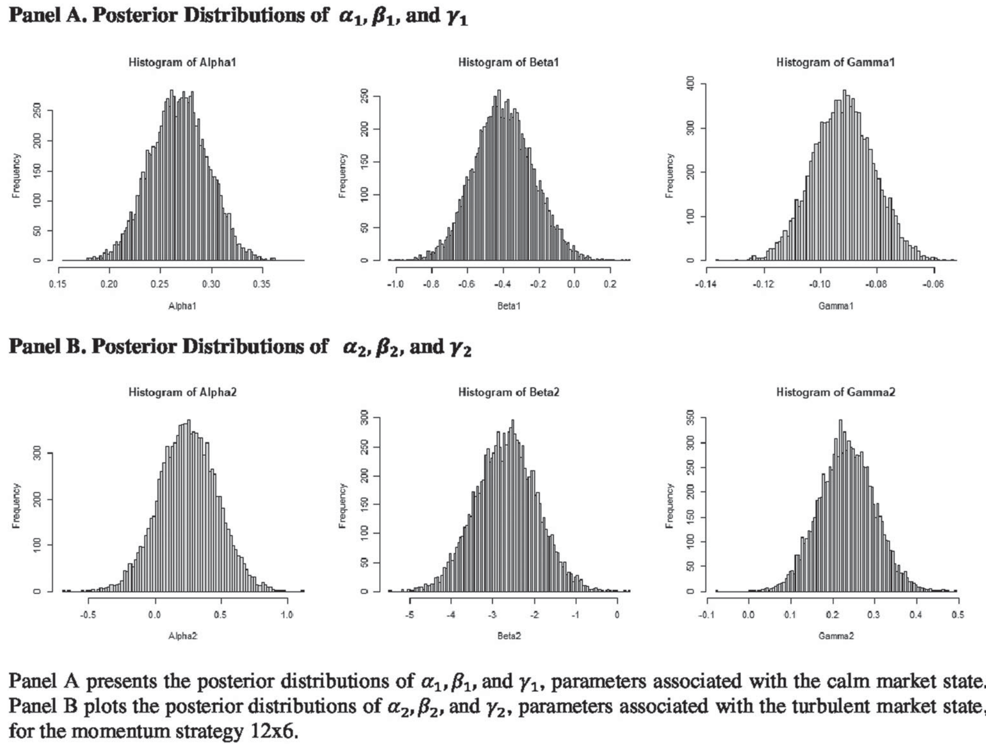


Figure 4. Posterior distributions of $\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2$, and γ_2.

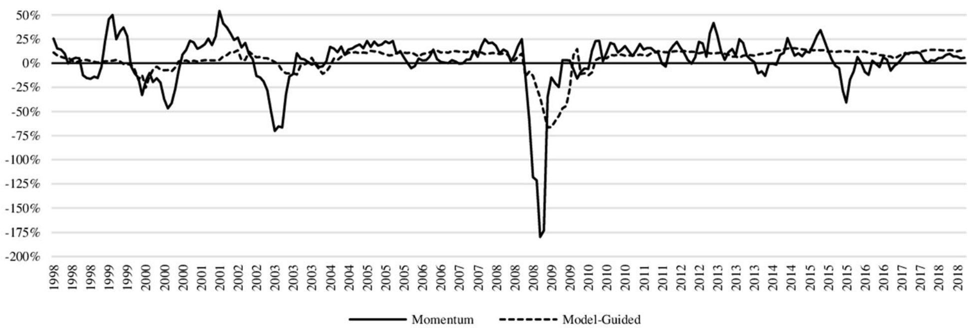
Figure 4 Panel B plots the posterior distributions of α_2, β_2, and γ_2, parameters associated with the turbulent market state, and they are very different from those of α_1, β_1, and γ_1.

The constant term α_2 is not significantly different from 0 as its 95% credibility interval is (−0.189, 0.664). The 95% credibility interval for β_2 is (−4.110, −1.233). It is worth noting that the RPMV not only has greater loading but also takes larger negative value than in the calm market state. Hence it can be said that the RPMV has considerably larger negative impact on the HPR in the turbulent market state than in the calm market state. The 95% credibility interval for γ_2 is (0.110, 0.360), which says that the RPR has significant positive impact on the HPR. According to these results, the momentum strategy is much more likely to produce losses in the turbulent market state and these losses could be large when high RPMV is combined with low RPR.

4.4. Out-of-sample predictability of momentum dynamics

The estimation results in Section 4.3 show that the RPMV, $vol_{\mathrm{t-12,t-1}}$, and the RPR, $r^P_{\mathrm{t-12,t-1}}$, have predictive power for the momentum return, $r^P_{t+1,t+6}$. In this section, we investigate the out-of-sample predictability of momentum dynamics using the two-regime switch model. Data from Jan 1969 to Dec1997 are used as a 'training' sample to obtain the posterior distributions of parameters, and the out-of-sample prediction starts from Jan 1998 and finishes at Aug 2018. The mean of the posterior predictive density is used as the expected HPR (see Appendix 2 for the algorithm for generating the density of future observations).

Figure 5 plots the mean of the posterior predictive density for the HPR, $E(r^P_{t+1,t+6})$, for each month during the out-of-sample test period Jan 1998–Aug 2018 and compares it with the monthly realised HPR, $r^P_{t+1,t+6}$. For all 248 observations, the two-regime switching model has a prediction success rate of 77%. Here we define prediction success as the mean of the posterior predictive density having the same sign as the realised HPR. The number of positive and negative observations of the HPR during Jan 1998–Aug 2018 are 172 and 76 respectively, and the prediction success rate is 91.9% for the former and 43% for the latter. The two-regime switching model



This figure compares the expected HPRs generated by the two-regime switching model and the realised HPRs for the momentum strategy 12x6 from Jan 1998 to Aug 2018.The mean of the posterior predictive density is used as the expected HPR.

Figure 5. Expected versus realised momentum returns.

does better in predicting larger losses. It has a prediction success rate of 60% (27 out of 45) for losses greater than 10%, and 76% (16 out of 21) for losses greater than 20%.

The two-regime switching model picks up the negative impact of extreme market exuberance, which is reflected by extremely high ranking period returns, on momentum returns that prior studies have failed to. It can be seen from Figure 5 that the momentum strategy generates sizable losses during the dot-com bubble until its peak in 2000, and the two-regime switching model successfully predicts these reversals.

A model-guided investment strategy is designed to exploit the predictability of momentum dynamics. It involves executing momentum trades, contrarian trades, or no trade based on the posterior predictive density of the HPR. The model-guided strategy 12×6 is implemented as follows. At the beginning of month t, the predictive density of the HPR is simulated based on the two-regime switching model. If 95% of its credibility interval lies in the positive domain, the momentum trade is executed; on the other hand, if 95% of its distribution lies in the negative territory, the contrarian trade is executed, that is, selling the winner portfolio, buying the loser portfolio, and holding this position for 6 months. When neither of the above is true, no trade takes place for that month. Over the out-of-sample test period, following this model-guided investment strategy, 199 momentum trades and 41 contrarian trades are executed. No action is taken for 8 of the 248 months. What is worth pointing out is that the model-guided strategy executes contrarian trades not just in the turbulent market state but also in the calm market state when the RPR is extremely high. This is therefore not the same dynamic strategy proposed in Dobrynskaya (2019) that switches to the contrarian trade one month after a significant market plunge, as defined by a market loss greater than 1.5 standard deviations below the mean market return.

Figure 6 compares the monthly HPR between the momentum strategy and the model-guided strategy for the out-of-sample test period. Overall, the model-guided strategy outperforms the momentum strategy. The model-guided strategy generates an average HPR of 12.5%, which is more than quadruple the average HPR (2.6%) of its momentum strategy counterpart. Its percentage of profitable trades is 77%, higher than 69%, the percentage of profitable trades of the momentum strategy. The model-guided strategy also has a lower percentage of losing trades (20%) than the momentum strategy (31%). The outperformance of the model-guided strategy results from the two-regime switching model being able to predict reversals associated with market exuberance in the calm market state as well as those associated with market panic in the turbulent market state.

5. Robustness check

We realise that research in this area requires rigorous robustness testing. In this study, we take four approaches to show that our findings are not results of data mining. First, we examine the estimation results of the two-regime switching model for a variety of momentum strategies with different ranking and holding periods. We also conduct performance comparison between winner and loser portfolios for different market states over the

This multiple-line chart compares the monthly HPR between the momentum strategy 12x6 and the model-guided strategy 12x6 from Jan 1998 to Aug 2018.

Figure 6. Performance comparison between momentum strategy and model-guided strategy.

whole sample period and check the consistency in the behaviour of the winner and the loser portfolio across different momentum strategies. We then go on to examine the out-of-sample performance for different momentum strategies over different sample periods. Finally, we apply the two-regime switching model to the US stock market and compare its performance between the UK and the USA, which has been the subject of far more attention in the literature.

5.1. Model estimation results

Altogether we add seven more momentum strategies for the robustness check, and we estimate the model with eight momentum strategies J ($=$ 3,6,9,12) $\times$ K ($=$ 3,6) for three sample periods, Jan 1969–Dec 1997, Jan 1969–Dec 2010, and Jan 1969–Sep 2019.

Table 4 reports the 95% credibility intervals for the parameters $\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2$, and γ_2 for all the eight momentum strategies across all three sample periods. What stands out is the consistency of α_1 and γ_1 across strategies over time. The 95% credibility intervals for α_1 are in the positive domain while those of γ_1 in the negative territory for all the eight strategies over all three sample periods. β_1 is not significantly differently from 0 except that it is significantly negative for momentum strategies 12×3 and 12×6 over the whole sample period. These results indicate the dominance of momentum effect in the calm market state. In this market state, market volatility is low, and its coefficient is not significantly different from 0, therefore, its impact on the HPR is negligible. Although the RPR has a significant negative impact on the HPR, the size of the negative impact is relatively small most of the time, compared with the size of α_1. As shown in Figure 2 Panel C, the RPR does spike occasionally, which can lead to momentum losses in the calm market state.

In the discussion of the estimation results of the parameters associated with the turbulent market state, we only consider the sample period of Jan 1969–Dec 2010 and the whole sample period.[10] According to the estimation results in Table 4, α_2 is not significantly different from zero except for moment strategies 9×3, 6×6 and 9×6, for which α_2 is significantly positive. Notably, the 95% credibility interval for β_2 is negative across all momentum strategies, and that β_2 tends to take large negative values. The results for γ_2 are also mixed. It is not significant for momentum strategies 3×3, 6×3 and 3×6; however, it is significantly positive for the other five momentum strategies. In the turbulent market state, the only parameter that displays consistency across different momentum strategies over time is the coefficient of the RPMV. The estimation results suggest that the RPMV is the only contributor to large momentum losses in this market state.

Although not reported in the table, the entire posterior distribution of τ lies within a narrow range and that of ϕ above 1 for all the eight momentum strategies for sample periods Jan 1969–Dec 2010 and Jan 1969–Sep 2019.

Overall, the estimation results support the validity of the conjecture that momentum portfolios perform significantly differently in different market states defined by the lagged market volatility. Momentum effect prevails in the short run in the calm market state; however, it can be replaced by contrarian effect when momentum portfolios generate extremely large returns over the holding period. In contrast, in the turbulent market state, contrarian effect dominates most of the time and its strength is positively associated with the lagged market volatility.

5.2. Performance comparison between winner and loser portfolio for different market states

We are also interested to know if the differences in the performance of the winner and loser portfolios between the calm and the turbulent market state reported in section 4 are consistent across different momentum strategies. Table 5 Panel A compares the average RPR for four different ranking periods, and Panel B the average HPR and the percentage of positive HPRs for the eight winner, loser, and momentum portfolios based on observations over the whole sample period Jan 1969–Sep 2019. Table 5 shows clear patterns in the performance differences of both winner and loser portfolios between the calm and the turbulent market state across different momentum strategies.

The number of observations in the turbulent market state varies from 50 to 62,[11] which is much smaller than that in the calm market state. According to Panel A, the RPR of both the winner and the loser portfolio tends to be lower in the turbulent market state than in the calm market state, however, these differences are relatively small. In contrast, there are stark differences in the performance of the winner and the loser portfolio over the holding period between the two market states, as revealed in Panel B. Both winner and loser portfolios perform better in the turbulent than in the calm market state as both have higher average HPRs and higher percentages of positive HPR observations.

The contrast in the performance of loser portfolios between the two market states is extraordinary. In every case, the loser portfolio's average HPR is in single digit in the calm market state and in double digits in the

Table 4. Model estimation results for sub-sample Periods 1969–1997, 1969–2010, and 1969–2019.

	α_1	β_1	γ_1	α_2	β_2	γ_2
Panel A: 1969–1997						
3 × 3	(0.085, 0.238)	(−1.394, 0.609)	(−0.210, −0.031)	(−0.266, 0.092)	(−1.607, 0.920)	(−0.066, 0.358)
6 × 3	(0.111,0. 204)	(−1.193, −0.185)	(−0.092, −0.024)	(−0.223, 0.023)	(−0.911, 0.565)	(0.0152, 0.199)
9 × 3	(0.110, 0.207)	(−0.908, −0.136)	(−0.072, −0.026)	(−0.343, 0.108)	(−0.676, −1.532)	(−0.103, 0.084)
12 × 3	(0.135, 0.224)	(−0.736, −0.196)	(−0.068, −0.035)	(−0.318, −0.171)	(−1.012, 0.905)	(−0.022, 0.106)
3 × 6	(0.085, 0.238)	(−1.394, 0.609)	(−0.210, −0.031)	(−0.266, 0.092)	(−1.607, 0.920)	(−0.066, 0.358)
6 × 6	(0.100, 0.266)	(−0.864, 0.908)	(−0.154, −0.044)	(−0.082, 0.118)	(−0.375, 0.601)	(−0.109, 0.020)
9 × 6	(0.061, 0.356)	(−1.251, 1.013)	(−0.137, −0.024)	(−0.310, 0.285)	(−1.146, 1.490)	(−0.140, 0.085)
12 × 6	(0.125, 0.381)	(−1.110, 1.147)	(−0.136, −0.075)	(0.093, 0.275)	(−0.882, −0.080)	(−0.098, 0.010)
Panel B: 1969–2010						
3 × 3	(0.066, 0.136)	(−0.499, 0.260)	(−0.135, −0.045)	(−0.097, 0.278)	(−2.452, −0.389)	(−0.053, 0.231)
6 × 3	(0.079, 0.149)	(−0.452, 0.133)	(−0.082, −0.030)	(−0.067, 0.424)	(−2.868, −0.779)	(−0.008, 0.226)
9 × 3	(0.072, 0.155)	(−0.345, 0.220)	(−0.068, −0.026)	(0.046, 0.554)	(−3.314, −1.335)	(0.068, 0.277)
12 × 3	(0.122, 0.206)	(−0.456, −0.063)	(−0.075, −0.044)	(−0.257, 0.420)	(−2.553, −0.422)	(0.080,0.245)
3 × 6	(0.093, 0.193)	(−0.790, 0.382)	(−0.167, −0.032)	(−0.089, 0.574)	(−4.307, −0.930)	(−0.192, 0.253)
6 × 6	(0.140, 0.257)	(−0.983, 0.158)	(−0.122, −0.045)	(0.306, 1.832)	(−10.457, −3.588)	(0.100, 0.611)
9 × 6	(0.184, 0.303)	(−0.784, 0.156)	(−0.123, −0.061)	(0.067, 1.163)	(−7.237, −3.004)	(0.227, 0.651)
12 × 6	(0.218, 0.346)	(−0.708, −0.10)	(−0.127, −0.081)	(−0.175, 0.662)	(−4.094, −1.211)	(0.097,0.355)
Panel C: 1969–2019						
3 × 3	(0.060, 0.121)	(−0.428, 0.242)	(−0.120, −0.039)	(−0.103, 0.243)	(−2.372, −0.397)	(−0.03, 0.234)
6 × 3	(0.078, 0.144)	(−0.467, 0.096)	(−0.078, −0.027)	(−0.015, 0.410)	(−2.730, −0.874)	(−0.011, 0.187)
9 × 3	(0.076, 0.150)	(−0.379, 0.131)	(−0.062, −0.023)	(0.044, 0.568)	(−3.345, −1.358)	(0.069, 0.275)
12 × 3	(0.117, 0.194)	(−0.467, −0.000)	(−0.067, −0.038)	(−0.323, 0.418)	(−2.564, −0.260)	(0.082, 0.252)
3 × 6	(0.087, 0.175)	(−0.799, 0.261)	(−0.141, −0.019)	(−0.065, 0.568)	(−4.249, −0.963)	(−0.189, 0.231)
6 × 6	(0.147, 0.246)	(−0.964, 0.003)	(−0.110, −0.041)	(0.365,1.874)	(−10.673, −3.924)	(0.130, 0.646)
9 × 6	(0.179, 0.285)	(−0.753, 0.002)	(−0.111, −0.056)	(0.072, 1.198)	(−7.378, −3.131)	(0.260, 0.664)
12 × 6	(0.213, 0.326)	(−0.736, −0.068)	(−0.114, −0.071)	(−0.189, 0.664)	(−4.110, −1.233)	(0.110, 0.360)

This table reports the 95% credibility intervals for α_1, β_1, γ_1, α_2, β_2, and γ_2 for momentum strategies J (= 3,6,9, 12) × K (= 3,6) for three sub-sample periods including Jan 1969–Dec 1997, Jan 1969–Dec 2010, and Jan 1969–Sep 2019.

turbulent market state. Moreover, loser portfolios have higher percentages of positive HPRs in the turbulent market state than in the calm market state. For example, the loser portfolio 9 × 6 generates an average HPR of 41.83% in the turbulent market state, which is 10 times higher than its average HPR of 3.91% in the calm market state. The HPR of this loser portfolio is positive 92% of the time in the turbulent market state, much higher than 58% in the calm market state. It is clear that the shift in the performance of loser portfolios explains the shift in the performance of momentum portfolios between the turbulent and the calm market state. Panel B also confirms that momentum strategies tend to generate profits (losses) when the lagged market volatility is low (high).

5.3. Out-of-sample predictive power of the two-regime switching model

In this section, we examine the robustness of the out-of-sample predictive power of the two-regime switching model. Table 6 compares the performance between model-guided strategies and their momentum strategy counterparts for three sub-sample periods Jan 1998–Dec 2005, Jan 2006–Dec 2012, and Jan 2013–Sep 2019.

Panel A reports the average HPRs, and Panel B the win/loss ratios. These results show that all model-guided strategies outperform their momentum strategy counterparts for the first two sub-sample periods with only one exception, the model-guided strategy 3 × 3, which has lower win/loss ratio than the momentum strategy 3 × 3 over the sub-sample period Jan 2006–Dec2012. For the last sub-sample period, all model-guided strategies produce the same performance as their momentum strategy counterparts.

Panel C compares the distributional characteristics of monthly HPRs over the entire out-of-sample test period. It is evident that model-guided strategies carry less risk than the momentum strategies. Each model-guided strategy has lower standard deviation, higher maximum HPR, and higher minimum HPR than its momentum strategy counterpart. Moreover, model-guided strategies' monthly HPRs are all positively skewed whereas momentum strategies' monthly HPRs are all negatively skewed.

5.4. Model performance in the US stock market

To further avoid the risk of data mining, we submit our model to the test of seeing how well it fits the data for the largest and most researched stock market, the US stock market.

Table 5. Momentum portfolio performance comparison between calm and turbulent market state.

	Calm market state			Turbulent market state		
	Winner	Loser	Momentum	Winner	Loser	Momentum
Panel A: Comparison of Ranking Period Return (in %)						
3-M	41.77	−23.34	65.11	38.08	−40.87	78.96
6-M	65.58	−30.89	96.47	57.18	−47.31	104.49
9-M	89.41	−36.12	125.55	69.16	−54.37	123.52
12-M	114.81	−39.97	154.79	86.53	−56.18	142.72
Panel B: Comparison of Holding Period Return (in %) and Percentage of Positive Holding Period Returns (in %)						
3 × 3	5.22 (71)	1.96 (57)	3.27 (72)	10.26 (73)	16.71 (69)	−6.44 (44)
6 × 3	5.88 (72)	1.49 (57)	4.40 (75)	9.18 (79)	18.06 (72)	−8.88 (38)
9 × 3	6.12 (75)	1.61 (56)	4.51 (77)	9.47 (78)	19.96 (70)	−10.49 (40)
12 × 3	6.03 (73)	1.63 (55)	4.39 (74)	8.45 (81)	18.30 (74)	−9.85 (45)
3 × 6	10.95 (74)	4.82 (61)	6.13 (76)	19.49 (87)	30.81 (81)	−11.32 (40)
6 × 6	12.39 (74)	3.99 (58)	8.40 (80)	17.01 (88)	32.92 (84)	−15.92 (38)
9 × 6	12.55 (73)	3.91 (58)	8.64 (78)	19.05 (96)	41.83 (92)	−22.78 (32)
12 × 6	11.69 (73)	4.30 (59)	7.39 (77)	16.83 (89)	37.22 (90)	−20.39 (31)

Note: This table reports performance comparison results for momentum portfolios between the calm and the turbulent market state over the whole sample period Jan 1969–Sep 2019. Panel A compares the average RPRs (in %) for four different ranking periods, and Panel B reports the average HPRs (in %) and the percentages of positive HPR observations (in %) in parentheses for the eight winner, loser, and momentum portfolios. The numbers of observations in the turbulent market state for momentum strategies of 3-month, 6-month, 9-month, and 12-month ranking period are 52, 58, 50, and 62, respectively.

Table 6. Performance comparison between momentum and model-guided strategies.

		3 × 3	6 × 3	9 × 3	12 × 3	3 × 6	6 × 6	9 × 6	12 × 6
Panel A: Mean Holding Period Return (%)									
1998–2005									
	Momentum	4.05	5.38	4.64	3.30	7.27	8.11	6.90	3.84
	Model-Guided	4.98	7.27	7.52	7.36	7.72	9.82	12.81	13.53
2006–2012									
	Momentum	0.63	0.13	0.33	0.21	0.13	−0.10	0.12	−0.68
	Model-Guided	5.17	5.85	8.14	8.83	8.22	14.91	18.75	17.40
2013–2019									
	Momentum	2.92	4.71	4.09	3.44	5.37	7.44	6.16	4.98
	Model-Guided	2.92	4.71	4.09	3.44	5.37	7.44	6.16	4.98
Panel B: Win/Loss Ratio									
1998–2005									
	Momentum	2.31	2.84	2.84	2.31	2.84	2.69	2.20	1.74
	Model-Guided	2.82	5.50	4.38	4.06	4.40	4.92	3.45	4.18
2006–2012									
	Momentum	2.36	1.90	2.11	2.36	2.36	2.65	2.36	2.65
	Model-Guided	2.16	2.29	2.68	3.42	3.11	3.00	5.00	5.00
2013–2019									
	Momentum	2.58	3.53	3.00	1.96	3.25	4.67	3.25	2.78
	Model-Guided	2.58	3.53	3.00	1.96	3.25	4.67	3.25	2.78
Panel C: Distributional Characteristics (1998-2019)									
Std.Dev	Momentum	0.124	0.150	0.162	0.161	0.193	0.247	0.271	0.269
	Model-Guided	0.115	0.132	0.147	0.143	0.175	0.212	0.234	0.234
Skewness	Momentum	−2.724	−3.400	−2.791	−2.693	−3.805	−4.122	−3.462	−3.363
	Model-Guided	2.189	3.287	2.612	2.551	1.605	4.575	3.720	3.513
Max. (%)	Momentum	38.8	30.8	49.6	33.2	41.2	53.9	71.7	54.1
	Model-Guided	80.8	109.1	112.6	106.2	138.9	174.3	183.0	179.6
Min. (%)	Momentum	−80.0	−109.1	−112.6	−106.2	−138.9	−174.3	−183.0	−179.6
	Model-Guided	−31.4	−30.9	−34.8	−33.1	−109.9	−30.6	−42.9	−50.0

Note: Panel A presents average HPRs and Panel B win/loss ratios (the number of winning trades/the number of losing trades) for the 8 pairs of trading strategies for three sample periods, Jan 1998–Dec 2005, Jan 2006–Dec 2012, and Jan 2013–Sep 2019. Panel C compares the distributional characteristics of monthly HPRs between model-guided strategies and their momentum strategy counterparts for the entire out-of-sample period.

In total, more than 8000 stocks are selected from all the domestic and primary stocks listed on the three main US stock exchanges-the NYSE, AMEX, and NASDAX from Jan 1970 to Dec 2018.[12] To alleviate the impact of illiquidity on momentum returns, we follow Jegadeesh and Titman (2001) and exclude all stocks priced below $5 at the beginning of the holding period. For comparison purposes, the same eight momentum strategies are implemented in the US stock market as before over the chosen sample period. To simplify the return computation procedure, firms with missing values either in the ranking period or in the holding period are all excluded.[13] The S&P 500 index is used as a proxy of the entire US stock market in measuring market volatility.

Table 7 presents the 95% credibility intervals for $\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2$, and γ_2 for the eight momentum strategies implemented in the US stock market during Jan 1970–Dec 2018.

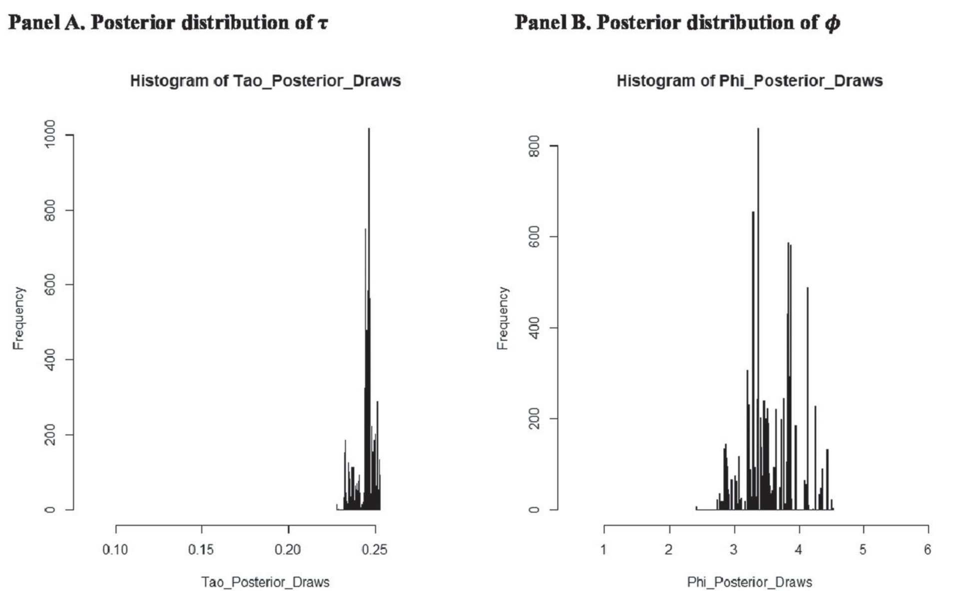
As shown in this table, the estimation results with the US data share many similarities with those reported in Table 4 for the UK stock market. What can be seen first is the consistency in the signs of the constant term, α_1, the coefficient of the RPR associated with the calm market state, γ_1, and the coefficient of the RPMV associated with the turbulent market state, β_2, across all the eight momentum strategies. Another pattern shared by Table 7 and Table 4 is that the constant term,α_2, and the coefficient of the RPR, γ_2, associated with the turbulent market state fail to retain their significance across different momentum strategies.

There is one prominent difference in the estimation results between the UK and the US. The coefficient of the RPMV associated with the calm market state, β_1, is significantly negative for seven momentum strategies in the US stock market whereas it is only the case for two momentum strategies in the UK stock market. This difference

Table 7. Model estimation results for the US stock market (Jan 1970–Dec 2018).

	α_1	β_1	γ_1	α_2	β_2	γ_2
3 × 3	(0.035, 0.105)	(−0.902, 0.028)	(−0.081, −0.012)	(0.004, 0.136)	(−1.086, −0.415)	(−0.077, 0.029)
6 × 3	(0.052, 0.104)	(−0.583, −0.021)	(−0.058, −0.012)	(−0.040, 0.394)	(−2.327, −1.095)	(−0.012, 0.216)
9 × 3	(0.084, 0.145)	(−0.631, −0.245)	(−0.049, −0.019)	(0.081, 0.792)	(−3.230, −1.681)	(−0.014, 0.207)
12 × 3	(0.078, 0.139)	(−0.488, −0.140)	(−0.043, −0.020)	(−0.403, 0.521)	(−2.131, −0.271)	(−0.020, 0.269)
3 × 6	(0.103, 0.177)	(−1.188, −0.329)	(−0.129, −0.049)	(0.159, 0.574)	(−4.404, −2.665)	(−0.080, 0.272)
6 × 6	(0.128, 0.204)	(−0.945, −0.240)	(−0.089, −0.038)	(0.406,1.528)	(−7.007, −3.993)	(−0.071, 0.343)
9 × 6	(0.162, 0.242)	(−0.786, −0.275)	(−0.091, −0.053)	(−0.018, 1.084)	(−5.174, −2.485)	(0.024, 0.379)
12 × 6	(0.158, 0.244)	(−0.812, −0.324)	(−0.077, −0.043)	(−0.830, 0.485)	(−3.159, −0.528)	(0.101, 0.546)

Note: This table reports the 95% credibility intervals for $\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2$, and γ_2 for momentum strategies J (= 3,6,9, 12) × K (= 3,6) implemented in the US stock market during Jan 1970–Dec 2018.



Panel A plots the posterior probability distribution of τ and Panel B plots that of ϕ for the sample period Jan 1970-Dec 2018. A uniform distribution with distribution support between 0.084 and 0.29 is assigned to τ as the prior probability distribution. A uniform distribution with distribution support between 0.5 and 6 is assigned to τ as the prior distribution. The posterior probability distributions of τ and ϕ are both generated by the independent Metropolis–Hastings algorithm with uniform candidate density.

Figure 7. Posterior distributions of τ and φ (momentum strategy 12×6 implemented in the US).

implies that the RPMV has significantly negative impact on momentum returns even in the calm market state in the US stock market, though as expected the magnitude of its negative impact is considerably smaller than that in the turbulent market state.

The posterior distributions of τ and ϕ are also similar to those for the UK stock market. Take the momentum strategy 12 × 6 as an example and the posterior distribution of τ (Figure 7 Panel A) clusters within a narrow range and the entire posterior distribution of ϕ (Figure 7 Panel B) lies above 2.5. What is worth pointing out is that the UK stock market is strongly correlated with the US stock market, and they tend to transition between the calm market state and the turbulent market state at the same time during the chosen sample period.

The above test results[14] with the US data show that the success of the two-regime switching model in capturing momentum dynamics is not exclusive to the UK stock market. The great similarity in the estimation results of the two-regime switching model between the UK and the USA indicates that investors in these two different geographical stock markets behave in a similar way, especially when facing dramatic increases in market volatility.

6. Discussion

Overall, the estimation results support the proposition that investor behaviour changes when the market transitions between low and high volatility market states, in a way that makes the performance of a momentum portfolio significantly different between the two market states.

When the lagged market volatility is relatively low, momentum portfolios are highly likely to generate profits. Interestingly, we find that the performance of a momentum portfolio over the holding period is inversely related to its performance over the ranking period: the higher the ranking period return, the lower the holding period return. Momentum losses in the calm market state are at least partially driven by extremely high ranking period returns. This finding is of significance as it challenges the risk-based explanations of momentum returns, which will be discussed in detail shortly.

Momentum portfolios tend to suffer large losses when the lagged market volatility is high. There is a significant negative relationship between the momentum portfolio's performance and the lagged market volatility over its ranking period when it exceeds a threshold level. This finding confirms the predictive power of lagged market volatility documented in the literature. Consistent with Wang and Xu (2015), we find those loser portfolios are responsible for momentum crashes. More specifically, we discover that large momentum losses in the turbulent market are not caused by winner portfolios losing value more than loser portfolios; instead, they are the result of loser portfolios gaining substantial amount of value as both winner and loser portfolios tend to perform better when the lagged market volatility is high than when it is low. These observations associated with high lagged market volatility are also difficult to explain in a rational expectation framework.

Momentum dynamics, especially large losses can be predicted to a great extent. The investment strategy guided by our model outperforms the momentum strategy and generates positively skewed monthly holding period return over the whole out-of-sample test period.[15] Our model-guided investment strategy shares similar functionalities to the dynamic momentum strategy proposed by Dobrynskaya (2019). Both strategies utilise a combination of momentum and contrarian trade and take advantage of the predictability of momentum losses; although Dobrynskaya (2019) exploits the predictability of the occurrence of momentum crashes after a significant market plunge whereas ours also capitalises on the predictability of the occurrence of momentum losses associated with market exuberance.

Our findings are not readily reconciled with the existing rational explanations of momentum. Under the assumption of rational expectation, the past return indicates relative risk level and hence is positively related to the future return. This inference seems to have support from cross-sectional studies. Bandarchuk and Hilscher (2013) find evidence that stocks with extreme characteristics tend to have more extreme past returns and that more extreme past returns result in higher momentum profits. As the association between stock characteristics and momentum returns is often interpreted in favour of a behavioural explanation of momentum, Bandarchuk and Hilscher (2013) argue that their findings may suggest otherwise. If the past return is indeed a proxy of risk, we should expect the same relationship between past returns and momentum profits in time series data as in cross-section data. However, our study found the opposite to be true in normal time as an inverse relationship between the two variables is found in the calm market state.

Vayanos and Woolley (2013) and Albuquerque and Miao (2014) provide rational expectations equilibrium models that generate both short-run momentum and long-run reversal effects in excess returns in a unified way. Vayanos and Woolley (2013) show that momentum and reversal can result from flows between investment funds in markets in which fund investors and managers are rational. In the event of a negative shock, investors who update negatively about the efficiency of the managers running these funds withdraw their investment, which trigger outflows, leading in turn to funds selling assets they own, and this further depresses the prices of the assets. Momentum arises if the outflows are gradual and trigger a gradual price decline and a drop in expected returns; reversal arises when outflows push prices below fundamental values, which eventually result in rising expected returns. Albuquerque and Miao (2014) propose a theory based on the hypothesis that there are two types of investors, informed and uninformed, trade in the financial market in a rational expectation framework. Informed investors possess advanced information about earnings as well as about the return on the private investment and can invest in both publicly traded assets and in a private investment opportunity, whereas an uninformed investor can invest in public assets only, and their information consists of past earnings and stock price realisations. In the set-up where private investment opportunities' returns are positively correlated with earnings, informed investors can profit by following trend-chasing strategies. As they also invest more in private investment opportunities, leading to more aggregate risk to be borne so that the risk premium rises. This generates short-run momentum. When the advanced information materialises, future excess returns fall, generating long-run reversals. Their models may provide plausible explanations for our findings associated with the calm market state; however, they are incapable of explaining the important role of market volatility in shifting momentum portfolio's performance and the 'large and sudden' reversals in the momentum effect when the lagged market volatility is extremely high.

Our findings can be loosely explained in the behavioural framework, and here we provide one possible behavioural explanation. As discussed in section 3.1, stock market volatility can shape investors' confidence and change their attitude towards risk. It is therefore reasonable to consider that investors are ambiguity-seeking and willing to invest in risky assets such as stocks in the calm market state. Moreover, studies show that investors tend to be overconfident and subject to biased self-attribution during their investment decision-making process. According to Daniel, Hirshleifer, and Subrahmanyam (1998), overconfidence combined with biased self-attribution leads to positive short-lag autocorrelations and negative long-lag autocorrelations, which implies that short-run positive return autocorrelations can be caused by under-reaction as well as continuing overreaction which results in correction. This could explain our finding of negative correlation between the RPR and the HPR in the calm market state as the larger the RPR is, the more likely the momentum portfolio is dominated by overreaction rather than underreaction during the ranking period, hence, lower HPR or even momentum reversal is expected during the subsequent holding period. In times when the stock market is volatile, investors allocate more attention to market information. Facing greater market-wide uncertainty, investors become ambiguity-averse, which leads them to reduce their investment in stocks. In more extreme cases, 'mass exodus' occurs from stocks that are deemed to be riskier than others, which results in these stocks being severely undervalued. Investors' flight from the stock market during volatile periods causes stocks to be underpriced in general, which can explain the better performance of both winner and loser portfolios in the turbulent market state than in the calm market state as underpricing during the ranking period is likely to be reversed during the subsequent holding period. Large momentum losses are the results of loser portfolios experiencing corrections of larger scale than winner portfolios during the holding period when the market recovers from turmoils.

The above explanation of significant momentum losses in the turbulent market state can find its support in the hypothesis of Griffin and Tversky (1992) that in revising their forecasts, investors focus too much on the strength of the evidence, and too little on its weight, relative to a rational Bayesian. Barberis, Shleifer, and Vishny (1998) argue that the Griffin and Tversky theory predicts that by holding the weight of information constant, news with more strength would generate a bigger reaction from investors. Specifically, holding the weight of information constant, one-time strong news events should generate an overreaction. They further suggest that one interpretation of stock prices bouncing back strongly in the few weeks after the crash of 1987 is investors' overreaction to the news of panic selling by other investors even without much firm-specific fundamental news.

7. Conclusion

This study extends the investigation of momentum dynamics conditional on market state defined by market volatility. We investigate the momentum effect in the UK stock market and find that it is a significant phenomenon with great variability over time. In line with the recent studies on momentum effect in the US stock, the most striking features of its dynamics are the occasional sharp reversal and its association with market volatility. Informed by the patterns in momentum time series data and psychological evidence of time-varying cognitive biases and heuristics, we construct a two-regime switching model with lagged market volatility as the switching variable to capture the dominance of momentum effect and occasional reversals in the stock market in the short run and show that it performs well in explaining the facts both within and out of sample.

We find a significant negative nonlinear relationship between the lagged market volatility and the momentum return, and a significant negative relationship between the past return and the momentum return in the calm market state. These relationships are robust across momentum strategies and over time. Momentum dynamics, especially the occasional sharp reversals, are highly predictable. Investment strategies that follow the prediction based on the two-regime switching model significantly outperform momentum strategies. The superior performance of the model-guided investment strategy in combination with the more favourable-to-investors distributional characteristics of its monthly holding period returns, particularly, the lower standard deviation and positive skewness, represents an anomaly which challenges the efficient market hypothesis.

Although we do not offer a conclusive explanation of our empirical results, we observe that behavioural models seem to be more capable than rational expectation models of explaining our findings. Nevertheless, there is no existing behavioural model that can generate sharp reversals with lagged market volatility playing a role. A model that incorporates time-varying attention allocation and time-varying ambiguity seeking conditional on market volatility state would appear to be required.

Notes

1. Barroso and Santa-Clara (2015) document that monthly realised volatility of momentum return has strong AR(1) correlation. Daniel and Moskowitz (2016) find that crashes are predictable using bear market indicators and ex ante market volatility estimates. Dobrynskaya (2019) shows that momentum returns tend to crash in 1–3 months after the stock market plunges.
2. For example, Grundy and Martin (2001) argue that stocks with higher/lower loadings on the stock-specific factors that performed relatively well during the ranking period are more likely to enter the winner/loser portfolio, and that the sign and the size of the strategy's investment period factor loadings reflect the sign and size of the factor realisations during the prior ranking period. Bandarchuk and Hilscher (2013) find evidence that stocks with extreme characteristics tend to have more extreme past returns and that more extreme past returns result in higher momentum profits.
3. For underreaction arguments, see, for example, Grinblatt and Han (2005); For overreaction arguments, see, for example, Daniel, Hirshleifer, and Subrahmanyam (1998); Hong and Stein (1999) argue for both underreaction and overreaction.
4. Although unreported, our tests went beyond 12 months, and the test results confirm that momentum is a short-term phenomenon.
5. Momentum strategies 6×3, 6×6, 12×3 and 12×6 are chosen because 6 and 12 months are popular choices for the duration of holding period in the literature and the profits of momentum strategies with 6- and 12-month ranking period tend to peak before or in the 6th month after implementation.
6. Data for Fama and French 3 factors, (RM-RF), SMB and HML, are from Xfi Centre and available at: http://business-school.exeter.ac.uk/research/centres/xfi/famafrench/files/. Data are only available for the period from Oct 1980 to Dec 2017. For more details on the construction of the factors, please see Gregory, Tharyan, and Christidis (2013).
7. FTSE All-Share index daily data are collected from DataStream.
8. Prior studies including Wang and Xu (2015), and Daniel and Moskowitz (2016) show that market volatility has predictive power for momentum dynamics in US stock market. In unreported results, Barroso and Santa-Clara (2015) find that the realised variance of the market in the previous six months produce prediction results for momentum returns as good as using momentum's own lagged risk.
9. Draws for τ and ϕ's posterior distribution are generated by Independent Metropolis–Hastings algorithm (for the details, please see Appendix 1).
10. There are far fewer volatile months for the sample period of Jan 1969–Dec 1997, and it results in small sample size in the high-volatility regime. This issue is reflected in the shape of the posterior distribution of τ. Instead of being clustered around a single value, it tends to be rather spread out.
11. Observations in the high-volatility regime are those with the RPMV greater than the minimum value of the support of posterior distribution of the threshold parameter . instead of the maximum value as in Section 4.
12. Individual stock data are collected from the Centre for Research in Security Prices (CRSP) through Wharton Research Data Services (WRDS).
13. By excluding firms with missing values in the holding period, our results suffer survivorship bias. However, it should not have significant impact on the performance of the two-regime switching model and the model-guided strategy.
14. We also tested the out-of-sample predictive power of the model with the US data and the results confirm the superior performance of the model-guided strategies over their momentum strategy counterparts. The results are available upon request.
15. In the currency markets, Copeland and Lu (2016) demonstrate that holding a value portfolio in times of high volatility earned excess returns. It would be interesting to examine the viability of replacing the contrarian portfolio with a value-based portfolio in the future research.

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Appendices

Appendix 1. Posterior distributions of Parameters

$$r^P_{t+1,t+K} = [1 - I_{[\tau,\infty)}(vol_{t-J,t-1})](\alpha_1 + \beta_1 vol_{t-J,t-1} + \gamma_1 r^P_{t-J,t-1}) + I_{[\tau,\infty)}(vol_{t-J,t-1})(\alpha_2 + \beta_2 vol_{t-J,t-1} + \gamma_2 r^P_{t-J,t-1}) + \varepsilon_t \quad \text{(A1)}$$

$$Var(\varepsilon_t) = \sigma_1^2[1 - I_{[\tau,\infty)}(vol_{t-J,t-1})] + \sigma_2^2 I_{[\tau,\infty)}(vol_{t-J,t-1}) \quad \text{(A2)}$$

Equation (A1) and Equation (A2) can be written in a compact form:

$$y_t = x'_t(\tau)\,\beta + \varepsilon_t \quad \text{(A3)}$$

$$Var(\varepsilon_t) = \sigma^2[(1 - I_{[\tau,\infty)}(vol_{t-J,t-1})) + \phi I_{[\tau,\infty)}(vol_{t-J,t-1})] = \sigma^2 h_t(\tau,\phi) \quad \text{(A4)}$$

where

$$y_t = r^P_{t+1,t+K} \quad \text{(A5)}$$

$$x'_t(\tau) = [1, vol_{t-J,t-1}, r^P_{t-J,t-1}, I_{[\tau,\infty)}(vol_{t-J,t-1}), I_{[\tau,\infty)}(vol_{t-J,t-1})*vol_{t-J,t-1},\ I_{[\tau,\infty)}(vol_{t-J,t-1})*r^P_{t-J,t-1}] \quad \text{(A6)}$$

$$\beta' = [\alpha_1, \beta_1, \gamma_1, (\alpha_2 - \alpha_1), (\beta_2 - \beta_1), (\gamma_2 - \gamma_1)] \quad \text{(A7)}$$

$$\sigma^2 = \sigma_1^2 \quad \text{(A8)}$$

$$\phi = \frac{\sigma_2^2}{\sigma_1^2} \in (0, +\infty] \quad \text{(A9)}$$

Define

$$y_t(\tau,\phi) = y_t/\sqrt{h_t(\tau,\phi)} \quad \text{(A10)}$$

$$\text{and } x'_t(\tau,\phi) = x'_t(\tau)/\sqrt{h_t(\tau,\phi)} \quad \text{(A11)}$$

Equation (A1) and Equation (A2) are transformed as:

$$y_t(\tau,\phi) = x'_t(\tau,\phi)\,\beta + \epsilon_t \quad \text{(A12)}$$

where

$$Var(\epsilon_t) = \sigma^2 = \sigma_1^2 \quad \text{(A13)}$$

Prior

$$\varphi(\beta,\sigma^2) \propto \sigma^{-2} \quad \text{(A14)}$$

$$\varphi(\phi) \propto I_{[\phi_L,\phi_H]}(\phi) \tag{A15}$$

$$\varphi(\tau) \propto I_{[z_L,z_H]}(\tau) \tag{A16}$$

Values of (ϕ_L, ϕ_H) and (z_L, z_H) are chosen using the method of trial and error. In addition, the number of observations per regime needs to be greater than the number of regressors.

The conditional posterior densities of β and σ^2 are given by

$$\varphi(\beta|\tau,\phi,y) = f_t(\beta|\beta_*(\tau,\phi), M_*(\tau,\phi), s_*(\tau,\phi), \nu) \tag{A17}$$

$$\varphi(\sigma^2|\tau,\phi,y) \propto f_{IG2}(\sigma^2|s_*(\tau,\phi),\nu) \tag{A18}$$

where

$$M_*(\tau,\phi) = \sum_{t=1}^{T} x_t(\tau,\phi)x_t'(\tau,\phi) \tag{A19}$$

$$\beta_*(\tau,\phi) = M_*^{-1}(\tau,\phi)\sum_{t=1}^{T} x_t(\tau,\phi)y_t(\tau,\phi) \tag{A20}$$

$$s_*(\tau,\phi) = \sum_{t=1}^{T} y_t(\tau,\phi)^2 - \beta_*'(\tau,\phi)M_*(\tau,\phi)\beta_*(\tau,\phi) \tag{A21}$$

$$\nu_* = T - K \tag{A22}$$

The corresponding posterior density of τ, ϕ is

$$\varphi(\tau,\phi|y) \propto \left[\prod_{t=1}^{T} h_t(\tau,\phi)\right]^{-1/2} s_*(\tau,\phi)^{-\nu_*/2}|M_*(\tau,\phi)|^{-1/2}\varphi(\tau)\varphi(\phi) \tag{A23}$$

The marginal posterior distributions ofϕ, τ can be obtained using one of numerical integration methods and Metropolis–Hastings algorithm with uniform distribution is employed in our estimation.

The marginal posterior densities of β and σ^2 follow with

$$\varphi(\beta|y) = \int\int \varphi(\beta|\tau,\phi,y)\varphi(\tau,\phi|y)d\tau d\phi \tag{A24}$$

$$\varphi(\sigma^2|y) = \int\int \varphi(\sigma^2|\tau,\phi,y)\varphi(\tau,\phi|y)d\tau d\phi \tag{A25}$$

Now that we have marginal posterior density for all parameter, we can obtain the Bayesian 90% credibility interval for each parameter as it is a continuous interval such that the posterior probability mass contained in that interval is 90%.

Appendix 2. Algorithm for generating the density of future observations

To form the predictive density of a momentum strategy's return, we follow the algorithm in Lubrano (1998). According to Lubrano (1998), the posterior expectation of this model corresponds to:

$$E[g(y^*)|Data] = E_\xi[E_{y^*}(g(y^*)|Data,\xi)] = \int_\xi \left[\int_R g(y^*)p(y^*|Data,\xi)dy^*\right]\varphi(\xi|Data)d\xi \tag{B1}$$

where $p(y^*|Data,\xi)$ is the density of future observations and ξ represents all the parameters of the model $\beta, \tau, \phi, \sigma^2$. For a given drawing of $\varepsilon^* = \varepsilon_{t+1}$ and conditionally onβ, τ, ϕ, generate y^* by recursion starting from:

$$y_{t+1} = \alpha_1 + \beta_1 x_t + (\alpha_2 - \alpha_1)I_{[\tau,\infty)} + (\beta_2 - \beta_1)I_{[\tau,\infty)}x_t + \varepsilon_{t+1} \tag{B2}$$

Conditional on τ, ϕ, the posterior densities of β, σ^2 are, respectively, Student and Inverted Gamma2. Consequently, a random drawing of βcan be obtained conditionally on σ^2 andτ, ϕ. Moreover, in order to take into account of the uncertainty of σ^2, a random drawing of ε is obtained from a Student density of T-k degrees of freedom, zero mean and scale parameters the conditional posterior mean of σ^2. All the needed ingredients now are available to evaluate the predictive moments of y in the same numerical integration loops used for the posterior moments of the parameters.

The algorithm to generate the density of future observations is as follows. For each point on the integration grid of τ, ϕ, we compute the conditional expectation $E[\sigma^2|Data,\tau,\phi]$ and compute the conditional moments of β; draw a value for ε from a $t(0, E[\sigma^2|Data,\tau,\phi], T-k)$ and a β from its conditional Student Posterior density; and then compute by recursion y^*. Finally, accumulate with the adequate weights of the Simpson rule$g(y^*)\varphi(\tau,\phi|Data)$.