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OPTIMAL TIME SERIES MOMENTUM

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ABSTRACT. We develop a continuous-time asset price model to capture the time series momentum documented recently. The underlying stochastic delay differential system facilitates the analysis of effects of different time horizons used by momentum trading. By studying an optimal asset allocation problem, we find that the performance of time series momentum strategy can be significantly improved by combining with market fundamentals and timing opportunity with respect to market trend and volatility. Furthermore, the results also hold for different time horizons, the out-of-sample tests and with short-sale constraints. The outperformance of the optimal strategy is immune to market states, investor sentiment and market volatility.

Key words: Momentum, reversal, portfolio choice, optimality, profitability.

JEL Classification: G12, G14, E32

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Optimal Time Series Momentum

Abstract

We develop a continuous-time asset price model to capture the time series momentum documented recently. The underlying stochastic delay differential system facilitates the analysis of effects of different time horizons used by momentum trading. By studying an optimal asset allocation problem, we find that the performance of time series momentum strategy can be significantly improved by combining with market fundamentals and timing opportunity with respect to market trend and volatility. Furthermore, the results also hold for different time horizons, the out-of-sample tests and with short-sale constraints. The outperformance of the optimal strategy is immune to market states, investor sentiment and market volatility.

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1. INTRODUCTION

Recently, Moskowitz, Ooi and Pedersen (2012) empirically investigate time series momentum (TSM) that characterizes strong positive predictability of a security's own past returns. This paper aims to theoretically examine how to optimally explore TSM in financial markets. We extend the standard geometric Brownian asset pricing model to incorporate a moving average momentum component and a mean-reverting fundamental component into the drift. By studying a dynamic asset allocation problem, we derive the optimal investment strategy of combining momentum and mean reversion in closed form, which includes pure momentum and pure mean-reverting strategies as special cases. To demonstrate the optimal performance of this strategy, we estimate the model to monthly returns of the S&P 500 index and use both the utility of portfolio wealth and Sharpe ratio to measure the performance of various trading strategies. We show that strategies based on the pure momentum and pure mean-reversion models cannot outperform the market but the optimal strategy of combining them can. We compare the performance of the optimal strategy with the TSM strategy used in Moskowitz et al. (2012) and show that the optimal strategy outperforms the TSM and passive holding strategies in the empirical literature. Essentially, in contrast to a TSM strategy based on trend only, the optimal strategy takes into account not only the trading signal based on momentum and fundamentals but also the size of position, which is associated with market volatility.

This paper contributes to the literature in three main ways. First, we find that the performance of TSM strategy can be significantly improved by combining with market fundamentals. To demonstrate the outperformance, we derive a suboptimal portfolio purely based on the TSM effect. We find that this portfolio is not able to outperform the market portfolio and the optimally combined portfolio. Without considering the fundamentals, the pure momentum portfolio is highly leveraged, and hence suffers from higher risks. For comparison, we also derive another suboptimal portfolio, the pure mean-reverting portfolio, by ignoring the TSM effect. We find that this portfolio is based conservatively on fundamental investments, leading to a stable growth rate of portfolio wealth, but is not able to explore the price trend, especially during extreme market periods, and hence underperforms the optimal portfolio. In addition to the above model-based results, we further investigate the model-free performance of the TSM. We construct the TSM portfolio following Moskowitz et al. (2012) to verify the theoretical analysis. We find that our optimal strategy outperforms the TSM strategy with respect to Sharpe ratio and cumulative excess return.

Second, to the best of our knowledge, this paper is the first to theoretically examine the time horizon effect on momentum trading. The time horizon plays a crucial

role in the performance of momentum strategies, which have been investigated extensively in the empirical literature.¹ However, due to the technical challenge, there are few theoretical results concerning the time horizon. The asset pricing model developed in this paper takes the time series momentum effect directly into account. Therefore historical prices underlying the time series momentum component affect asset prices, resulting in a non-Markov process characterized by stochastic delay differential equations (SDDEs). This is very different from the Markov asset price process documented in the literature (Merton 1969, 1971) in which it is difficult to model the time series momentum strategy explicitly. In the case of Markov processes, the stochastic control problem is most frequently solved using the dynamic programming method and HJB equation. However, solving the optimal control problem for SDDEs using the dynamic programming method becomes more challenging because it involves infinite-dimensional partial differential equations. The only other way to solve the problem is to apply a type of Pontryagin maximum principle, which was developed recently by Chen and Wu (2010) and Øksendal et al. (2011) for the optimal control problem of SDDEs. By exploring these latest advances in the theory of the maximum principle for control problems of SDDEs, we derive the optimal strategies in closed form. This helps us to study thoroughly the impact of historical information on the profitability of different strategies based on different time horizons, in particular of time series momentum trading strategies based on moving averages over different time horizons.

Third, we show that, in addition to price trend, position size is another very important factor for momentum trading. The optimal position size derived in this paper is determined by the level of trading signals and market volatility. In the empirical literature, momentum trading only considers the trading signals of price trend and takes a constant position to trade. We show that, if we only consider the sign of trading signals indicated by the optimal strategy and take a unit position to trade, the portfolio is not able to outperform the optimal portfolio for all time horizons. The robustness of the performance of the optimal strategy is also tested for different sample periods, out-of-sample predictions, short-sale constraints, market states, investor sentiment and market volatility.

This paper is closely related to the literature on reversal and momentum, two of the most prominent financial market anomalies. Reversal is the empirical observation that assets performing well (poorly) over a long period tend subsequently to underperform (outperform). Momentum is the tendency of assets with good (bad) recent performance to continue outperforming (underperforming) in the short term. Reversal and momentum have been documented extensively for a wide variety of assets. On the one hand, Fama and French (1988) and Poterba and Summers (1988),

¹See, for example, De Bondt and Thaler (1985) and Jegadeesh and Titman (1993).

among many others, document reversal for holding periods of more than one year, which induces negative autocorrelation in returns.² The value effect documented in Fama and French (1992) is closely related to reversal, whereby the ratio of an asset's price relative to book value is negatively related to subsequent performance. Mean reversion in equity returns has been shown to induce significant market timing opportunities (Campbell and Viceira 1999, Wachter 2002 and Koijen, Rodríguez and Sbuelz 2009). On the other hand, the literature mostly studies cross-sectional momentum.³ More recently, Moskowitz et al. (2012) investigate TSM that characterizes strong positive predictability of a security's own past returns. For a large set of futures and forward contracts, Moskowitz et al. (2012) find that TSM based on excess returns over the past 12 months persists for between one and 12 months then partially reverses over longer horizons. They provide strong evidence for TSM based on the moving average of look-back returns. This effect based purely on a security's own past returns is related to, but different from, the cross-sectional momentum phenomenon studied extensively in the literature. Through return decomposition, Moskowitz et al. (2012) argue that positive auto-covariance is the main driving force for TSM and cross-sectional momentum effects, while the contribution of serial cross-correlations and variation in mean returns is small. Intuitively, a strategy taking into account both the short-run momentum and long-run mean reversion in time series should be profitable and outperform pure momentum and pure mean-reversion strategies. This paper establishes a model to justify this intuition theoretically and empirically.

The apparent persistent and sizeable profits of strategies based on momentum and reversal have attracted considerable attention, and many studies have tried to explain the phenomena.⁴ Extending the literature, this paper develops an asset price model by taking both mean reversion and time series momentum directly

²For instance, Jegadeesh (1991) finds that the next one-month returns can be negatively predicted by their lagged multiyear returns. Lewellen (2002) shows that the past one-year returns negatively predict future monthly returns for up to 18 months.

³Jegadeesh and Titman (1993) document cross-sectional momentum for individual U.S. stocks, predicting returns over horizons of 3–12 months using returns over the past 3–12 months. The evidence has been extended to stocks in other countries (Fama and French 1998), stocks within industries (Cohen and Lou 2012), across industries (Cohen and Frazzini 2008), and the global market with different asset classes (Asness, Moskowitz and Pedersen 2013).

⁴Among which, the three-factor model of Fama and French (1996) can explain long-run reversal but not short-run momentum. Barberis, Shleifer and Vishny (1998) argue that these phenomena are the result of the systematic errors investors make when they use public information to form expectations of future cash flows. Models Daniel, Hirshleifer and Subrahmanyam (1998), with single representative agent, and Hong and Stein (1999), with different trader types, attribute the under reaction to overconfidence and overreaction to biased self-attribution. Barberis and Shleifer (2003) show that style investing can explain momentum and value effects. Sagi and Seasholes

into account and demonstrates the explanatory power of the model through the outperformance of the optimal strategy.

This paper is largely motivated by the empirical literature testing trading signals with combinations of momentum and reversal.⁵ Asness, Moskowitz and Pedersen (2013) highlight that studying value and momentum jointly is more powerful than examining each in isolation.⁶ Huang, Jiang, Tu and Zhou (2013) find that both mean reversion and momentum can coexist in the S&P 500 index over time. In this paper, we show theoretically that a combined TSM and reversal strategy is optimal. This paper is also inspired by Koijen, Rodríguez and Sbuelz (2009), who propose a theoretical model in which stock returns exhibit momentum and mean-reversion effects. They study the dynamic asset allocation problem with constant relative risk aversion (CRRA) utility. This paper differs from Koijen et al. (2009) in two respects. First, our modelling of TSM is different. In Koijen et al. (2009), the momentum is calculated from the entire set of historical returns with geometrically decaying weights. This effectively reduces the pricing dynamics to a Markovian system, but it is difficult to explicitly study the impacts of different look-back periods on momentum-related trading strategies. In this paper, we measure momentum by the standard moving average over a moving window with a fixed look-back period, which is consistent with the momentum literature. Second, our focuses are different. Koijen et al. (2009) focus on the performance of the hedging demand implied by the model. In our paper we focus on the performance of the optimal strategy compared to the market, TSM, and mean-reversion trading strategies.

The paper is organized as follows. We first present the model and derive the optimal asset allocation in Section 2. In Section 3, we estimate the model to the S&P 500 and conduct a performance analysis of the optimal portfolio. We then investigate the time horizon effect in Section 4. Section 5 concludes. All the proofs and the robustness analysis are included in the appendices.

2. THE MODEL AND OPTIMAL ASSET ALLOCATION

In this section, we introduce an asset price model and study the optimal investment decision problem. We consider a financial market with two tradable securities,

(2007) present an option model to identify observable firm-specific attributes that drive momentum. Vayanos and Woolley (2013) show that slow-moving capital can also generate momentum.

⁵For example, Balvers and Wu (2006) and Serban (2010) show empirically that a combination of momentum and mean-reversion strategies can outperform pure momentum and pure mean-reversion strategies for equity markets and foreign exchange markets respectively.

⁶They find that separate factors for value and momentum best explain the data for eight different markets and asset classes. Furthermore, they show that momentum loads positively and value loads negatively on liquidity risk; however, an equal-weighted combination of value and momentum is immune to liquidity risk and generates substantial abnormal returns.

a riskless asset B satisfying

$$\frac{dB_t}{B_t} = r dt \quad (2.1)$$

with a constant riskless rate r , and a risky asset. Let S_t be the price of the risky asset or the level of a market index at time t where dividends are assumed to be reinvested. Empirical studies on return predictability, see for example Fama (1991), have shown that the most powerful predictive variables of future stock returns in the United States are past returns, dividend yield, earnings/price ratio, and term structure variables. Following this literature and Kojien et al. (2009), we model the expected return by a combination of a momentum term m_t based on the past returns and a long-run mean-reversion term μ_t based on market fundamentals such as dividend yield. Consequently, we assume that the stock price S_t follows

$$\frac{dS_t}{S_t} = [\phi m_t + (1 - \phi)\mu_t]dt + \sigma'_S dZ_t, \quad (2.2)$$

where ϕ is a constant, measuring the weight of the momentum component m_t , σ_S is a two-dimensional volatility vector (and σ'_S stands for the transpose of σ_S), and Z_t is a two-dimensional vector of independent Brownian motions. The uncertainty is represented by a filtered probability space $(\Omega, \mathcal{F}, P, \{\mathcal{F}_t\}_{t \geq 0})$ on which the two-dimensional Brownian motion Z_t is defined. As usual, the mean-reversion process μ_t is defined by an Ornstein-Uhlenbeck process,

$$d\mu_t = \alpha(\bar{\mu} - \mu_t)dt + \sigma'_\mu dZ_t, \quad \alpha > 0, \quad \bar{\mu} > 0, \quad (2.3)$$

where $\bar{\mu}$ is the constant long-run expected return, α measures the rate at which μ_t converges to $\bar{\mu}$, and σ'_μ is a two-dimensional volatility vector. The momentum term m_t is defined by a standard moving average (MA) of past returns over $[t - \tau, t]$,

$$m_t = \frac{1}{\tau} \int_{t-\tau}^t \frac{dS_u}{S_u}, \quad (2.4)$$

where delay τ represents the time horizon. The way we model the momentum in this paper is motivated by the TSM strategy documented recently in Moskowitz et al. (2012), who demonstrate that the average return over a past period (say, 12 months) is a positive predictor of future returns, especially the return for the next month. This is different from Kojien et al. (2009), in which the momentum M_t at time t is defined by

$$M_t = \int_0^t e^{-w(t-u)} \frac{dS_u}{S_u},$$

which is a geometrically decaying weighted sum of the past returns over $[0, t]$. The advantage of M_t is that the resulting price process is a Markovian process. However, it suffers from some drawbacks. First, M_t is not a weighted average since the weights over $[0, t]$ do not sum to 1. Second, M_t is not a moving average of past returns with a fixed time horizon as commonly used in the empirical literature on momentum.

Third, the return process and the momentum variable in the discretization of Koijen et al.'s model have the same expression.⁷ On the other hand, the momentum m_t introduced in (2.4) overcomes these drawbacks. It is a standard moving average over a moving window $[t-\tau, t]$ with a fixed look-back period of $\tau(>0)$ and the weights sum to 1. It is also consistent with momentum strategies used in the empirical literature that explore price trends based on the average returns over a fixed look-back period. The resulting asset price model (2.2)–(2.4) is characterized by a stochastic delay integro-differential system, which is non-Markovian and lacks analytical tractability. We show in Appendix A that the price process of (2.2)–(2.4) almost surely has a unique continuously adapted pathwise solution and the asset price stays positive for given positive initial values over $[-\tau, 0]$.

We now consider a typical long-term investor who maximizes the expected utility of terminal wealth at time $T(>t)$. Let W_t be the wealth of the investor at time t and π_t be the fraction of the wealth invested in the stock. Then it follows from (2.2) that the change in wealth satisfies

$$\frac{dW_t}{W_t} = \{\pi_t[\phi m_t + (1-\phi)\mu_t - r] + r\}dt + \pi_t\sigma'_S dZ_t. \quad (2.5)$$

We assume that the preferences of the investor can be represented by a CRRA utility index with a constant coefficient of relative risk aversion equal to γ . The investment problem of the investor is then given by

$$J(W, m, \mu, t, T) = \sup_{(\pi_u)_{u \in [t, T]}} \mathbb{E}_t \left[\frac{W_T^{1-\gamma} - 1}{1-\gamma} \right], \quad (2.6)$$

where $J(W, m, \mu, t, T)$ is the value function corresponding to the optimal investment strategy. We apply the maximum principle for optimal control of stochastic delay differential equations and derive the optimal investment strategy in closed form. The result is presented in the following proposition and the proof can be found in Appendix B.

Proposition 2.1. *For an investor with an investment horizon $T-t$ and constant coefficient of relative risk aversion γ , the optimal wealth fraction invested in the risky asset is given by*

$$\pi_u^* = \frac{\phi m_u + (1-\phi)\mu_u - r}{\sigma'_S \sigma_S} + \frac{(z_u)_3 \sigma_S}{p_u^3 \sigma'_S \sigma_S}, \quad (2.7)$$

where z_u and p_u are governed by a backward stochastic differential system (B.6) in Appendix B.2. Especially, when $\gamma = 1$, the preference is characterized by a log utility

⁷As a result, there is an identification problem. To solve the problem, Koijen et al. (2009) estimate the model using a restricted maximum likelihood method to ensure that the model implied autocorrelation fits the empirical autocorrelation structure of stock returns.

and the optimal allocation to stocks is given by

$$\pi_t^* = \frac{\phi m_t + (1 - \phi)\mu_t - r}{\sigma'_S \sigma_S}. \quad (2.8)$$

This proposition states that the optimal fraction (2.7) invested in the stock consists of two components. The first characterizes the myopic demand for the stock and the second is the intertemporal hedging demand (see, for instance, Merton 1971). When $\gamma = 1$, the optimal strategy (2.8) characterizes the myopic behavior of the investor with log utility. This result has a number of implications. First, when the asset price follows a geometric Brownian motion process with mean-reversion drift μ_t , namely $\phi = 0$, the optimal investment strategy (2.8) becomes

$$\pi_t^* = \frac{\mu_t - r}{\sigma'_S \sigma_S}. \quad (2.9)$$

This is the optimal investment strategy with mean-reverting returns obtained in the literature, say for example Campbell and Viceira (1999) and Wachter (2002). In particular, when $\mu_t = \bar{\mu}$ is a constant, the optimal portfolio (2.9) collapses to the optimal portfolio of Merton (1971).

Second, when the asset return depends only on the momentum, namely $\phi = 1$, the optimal portfolio (2.8) reduces to

$$\pi_t^* = \frac{m_t - r}{\sigma'_S \sigma_S}. \quad (2.10)$$

If we consider a trading strategy based on the trading signal indicated by the excess return $m_t - r$ only, with $\tau = 12$ months, the strategy of long/short when the trading signal is positive/negative is consistent with the TSM strategy used in Moskowitz et al. (2012). By constructing portfolios based on monthly excess returns over the past 12 months and holding for one month, Moskowitz et al. (2012) show that this strategy performs the best among all the momentum strategies with look-back and holding periods varying from one month to 48 months. Therefore, if we only take fixed long/short positions and construct simple buy-and-hold momentum strategies over a large range of look-back and holding periods, (2.10) shows that the TSM strategy of Moskowitz et al. (2012) can be optimal when mean reversion is not significant in financial markets. On the one hand, this provides a theoretical justification for the TSM strategy when market volatilities are constant and returns are not mean-reverting. On the other hand, note that the optimal portfolio (2.10) also depends on volatility. This explains the dependence of momentum profitability on market conditions and volatility found in empirical studies. In addition, the optimal portfolio (2.10) defines the optimal wealth fraction invested in the risky asset. Hence the TSM strategy of taking fixed positions based on the trading signal may not be optimal in general.

Third, the optimal strategy (2.8) implies that a weighted average of momentum and mean-reverting strategies is optimal. Intuitively, it takes into account the short-run momentum and long-run reversal, both well-supported market phenomena. It also takes into account the timing opportunity with respect to market trend and volatility.

In summary, for the first time, we have provided theoretical support for optimal strategies that combining of momentum and reversal in a simple asset price model. The simple model and closed-form optimal strategy (2.8) facilitate model estimation and empirical analysis. In the rest of the paper, we assume $\gamma = 1$.⁸ We first estimate the model to the S&P 500 and then evaluate and demonstrate empirically the performance of the optimal strategy comparing it to the market and other trading strategies recorded in the literature.

3. MODEL ESTIMATION AND PERFORMANCE ANALYSIS

In this section we first estimate the model to the S&P 500. Based on these estimations, we then use utility of portfolio wealth and the Sharpe ratio to examine the performance of the optimal strategy (2.8), comparing it to the performance of the market index and the optimal strategies based on pure momentum and pure mean-reversion models. To provide further evidence, we conduct out-of-sample tests on the performance of the optimal strategy and examine the effect of short sale constraints, market states, sentiment and volatility. In addition, we also compare the performance of the optimal strategy to that of the TSM strategy.

3.1. Model Estimation. In line with Campbell and Viceira (1999) and Kojien et al. (2009), the mean-reversion variable is affine in the (log) dividend yield,

$$\mu_t = \bar{\mu} + \nu(D_t - \mu_D) = \bar{\mu} + \nu X_t,$$

where ν is a constant, D_t is the (log) dividend yield with $\mathbb{E}(D_t) = \mu_D$, and $X_t = D_t - \mu_D$ denotes the de-measured dividend yield. Thus the asset price model (2.2)-(2.4) becomes

$$\begin{cases} \frac{dS_t}{S_t} = [\phi m_t + (1 - \phi)(\bar{\mu} + \nu X_t)] dt + \sigma'_S dZ_t, \\ dX_t = -\alpha X_t dt + \sigma'_X dZ_t, \end{cases} \quad (3.1)$$

where $\sigma_X = \sigma_\mu / \nu$. The uncertainty in system (3.1) is driven by two independent Brownian motions. Without loss of generality, we follow Sangvinatsos and Wachter

⁸For $\gamma \neq 1$, the optimal portfolio (2.7) can be solved numerically, which leads to further estimation errors when estimating the model. To reduce estimation error and have a better understanding of the results, we take the advantage of the closed-form solution and consider $\gamma = 1$.

(2005) and assume the Cholesky decomposition on the volatility matrix Σ of the dividend yield and return,

$$\Sigma = \begin{pmatrix} \sigma'_S \\ \sigma'_X \end{pmatrix} = \begin{pmatrix} \sigma_{S(1)} & 0 \\ \sigma_{X(1)} & \sigma_{X(2)} \end{pmatrix}.$$

Thus, the first element of Z_t is the shock to the return and the second is the dividend yield shock that is orthogonal to the return shock.

To be consistent with the momentum and reversal literature, we discretize the continuous-time model (3.1) at a monthly frequency. This results in a bivariate Gaussian vector autoregressive (VAR) model on the simple return⁹ and dividend yield X_t ,

$$\begin{cases} R_{t+1} = \frac{\phi}{\tau}(R_t + R_{t-1} + \cdots + R_{t-\tau+1}) + (1 - \phi)(\bar{\mu} + \nu X_t) + \sigma'_S \Delta Z_{t+1}, \\ X_{t+1} = (1 - \alpha)X_t + \sigma'_X \Delta Z_{t+1}. \end{cases} \quad (3.2)$$

Note that both R_t and X_t are observable. We use monthly S&P 500 data over the period January 1871—December 2012 from the home page of Robert Shiller (www.econ.yale.edu/~shiller/data.htm) and estimate model (3.2) using the maximum likelihood method. We set the instantaneous short rate $r = 4\%$ annually. As in Campbell and Shiller (1988a, 1988b), the dividend yield is defined as the log of the ratio between the last period dividend and the current index. The total return index is constructed by using the price index series and the dividend series.

The estimations are conducted separately for given time horizon τ varying from one to 60 months. Empirically, Moskowitz et al. (2012) show that the TSM strategy based on a 12-month horizon better predicts the next month's return than other time horizons. Therefore, in this section, we focus on the performance of the optimal strategy with a look-back period of $\tau = 12$ months and a one-month holding period. The effect of time horizon τ varying from one to 60 months is studied in the next section.

For comparison, we estimate the full model (FM) (3.2) with $\phi \neq 0$, the pure momentum model (MM) with $\phi = 1$, and the pure mean-reversion model (MRM) with $\phi = 0$. For $\tau = 12$, Table 3.1 reports the estimated parameters, together with the 95% confidence bounds. For the pure momentum model ($\phi = 1$), there is only one parameter $\sigma_{S(1)}$ to be estimated. For the full model, as one of the key parameters, it shows that the momentum effect parameter $\phi \approx 0.2$, which is significantly different from zero. This implies that market index can be explained by about 20% of the momentum component and 80% of the mean-reverting component. Other parameter

⁹To be consistent with the momentum and reversal literature, we use simple return to construct m_t and also discretize the stock price process into simple return rather than log return.

TABLE 3.1. Parameter estimations of the full model (FM), pure momentum model (MM) with $\tau = 12$, and pure mean-reversion model (MRM).

Parameter	α	ϕ	$\bar{\mu}$	ν
FM (%)	0.46	19.85	0.36	0.20
Bounds (%)	(0.03, 0.95)	(8.70, 31.00)	(0.26, 0.46)	(-0.60, 1.00)
MM (%)				
Bounds (%)				
MRM (%)	0.55		0.37	$2.67 * 10^{-5}$
Bounds (%)	(0.07, 1.03)		(0.31, 0.43)	(-0.46, 0.46)
Parameters	$\sigma_{S(1)}$	$\sigma_{X(1)}$	$\sigma_{X(2)}$	
FM (%)	4.10	-4.09	1.34	
Bounds (%)	(3.95, 4.24)	(-4.24, -3.93)	(1.29, 1.39)	
MM (%)	4.23			
Bounds (%)	(4.09, 4.38)			
MRM (%)	4.11	-4.07	1.36	
Bounds (%)	(3.97, 4.25)	(-4.22, -3.92)	(1.32, 1.40)	

estimates in terms of the level and significance in Table 3.1 are consistent with those in Kojien et al. (2009).

We also conduct a log-likelihood ratio test to compare the full model to the pure momentum model ($\phi = 1$) and pure mean-reversion model ($\phi = 0$). For the pure momentum model, the test statistic (13100) is much greater than 12.59, the critical value with six degrees of freedom at the 5% significance level. For the pure mean-reversion model, the test statistic (6200) is much greater than 3.841, the critical value with one degree of freedom at 5% significance level. Therefore the full model is significantly better than the pure momentum model and the pure mean-reversion model. This implies that the (full) model captures short-term momentum and long-term reversion in the market index and fits the data better than the pure momentum and pure mean-reverting models.

3.2. Economic Value. Based on the previous estimations, we examine the economic value of the optimal portfolio in terms of the utility of the portfolio wealth, comparing it to those of the market index and of the pure momentum and pure mean-reversion models. We evaluate the performance of a portfolio (or strategy) in terms of the Sharpe ratio in the next section. In the following performance analysis, we focus on the log utility preference for the investor.¹⁰

¹⁰Since the model is non-Markovian, the optimal investment strategy for CRRA utility functions in general involves a system of full-coupled forward-backward stochastic differential equations

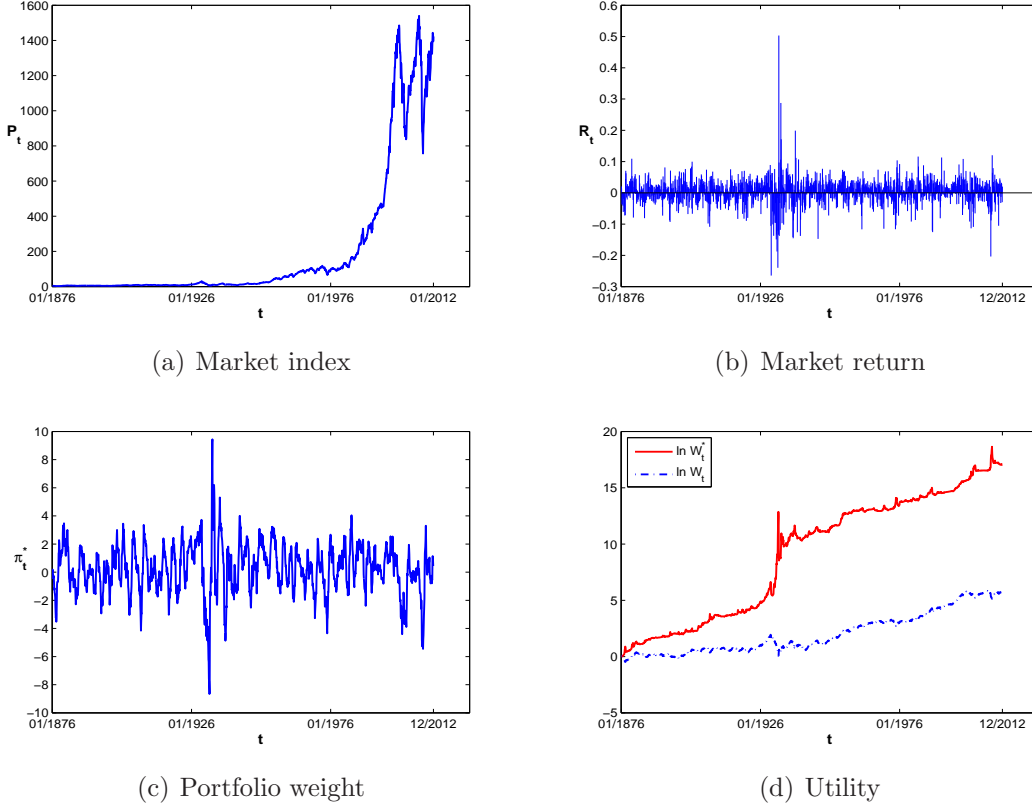


FIGURE 3.1. The time series of market index (a), the simple return of the S&P 500 (b); and the time series of the optimal portfolio (c) and the utility (d) of the optimal portfolio wealth from January 1876 until December 2012 for $\tau = 12$. In (d), the utilities of the optimal portfolio wealth and the market index are plotted in solid red and dash-dotted blue lines respectively.

We first compare the realized utility of the optimal portfolio wealth invested in the S&P 500 index based on the optimal strategy (2.8) with a look-back period $\tau = 12$ months and one-month holding period to the utility of a passive holding investment in the S&P 500 index with an initial wealth of \$1. As a benchmark, the log utility of an investment of \$1 to the index from¹¹ January 1876 to December 2012 is equal to 5.765. For $\tau = 12$, we calculate the moving average m_t of past 12-month returns

(FBSDEs), which are difficult to deal with analytically and are usually analyzed numerically. For analytical tractability and to avoid simulation errors, we consider log utility when examining the performance of the optimal strategy. We show that even the optimal strategy associated with log utility can significantly outperform the TSM strategy and the market index. But due to the above limitation, the effect of hedging demand is not considered here and left for future research.

¹¹Considering the robustness analysis for τ varying from one to 60 months in the next section, all the portfolios start at the end of January 1876 (60 months after January 1871).

at any point of time based on the market index from January 1876 to December 2012. With an initial wealth of \$1 at January 1876 and the estimated parameters in Table 3.1, we calculate the monthly investment of the optimal portfolio wealth W_t based on (2.8) and record the realized utilities of the optimal portfolio wealth from January 1876 to December 2012. Based on the calculation, we plot the index level and simple return of the S&P 500 index from January 1876 until December 2012 in Fig. 3.1 (a) and (b). Fig. 3.1 (c) reports the optimal wealth fractions π_t of (2.8) and Fig. 3.1 (d) reports the evolution of the utilities of the optimal portfolio wealth over the same time period, showing that the optimal portfolios outperform the market index measured by the utility of wealth.

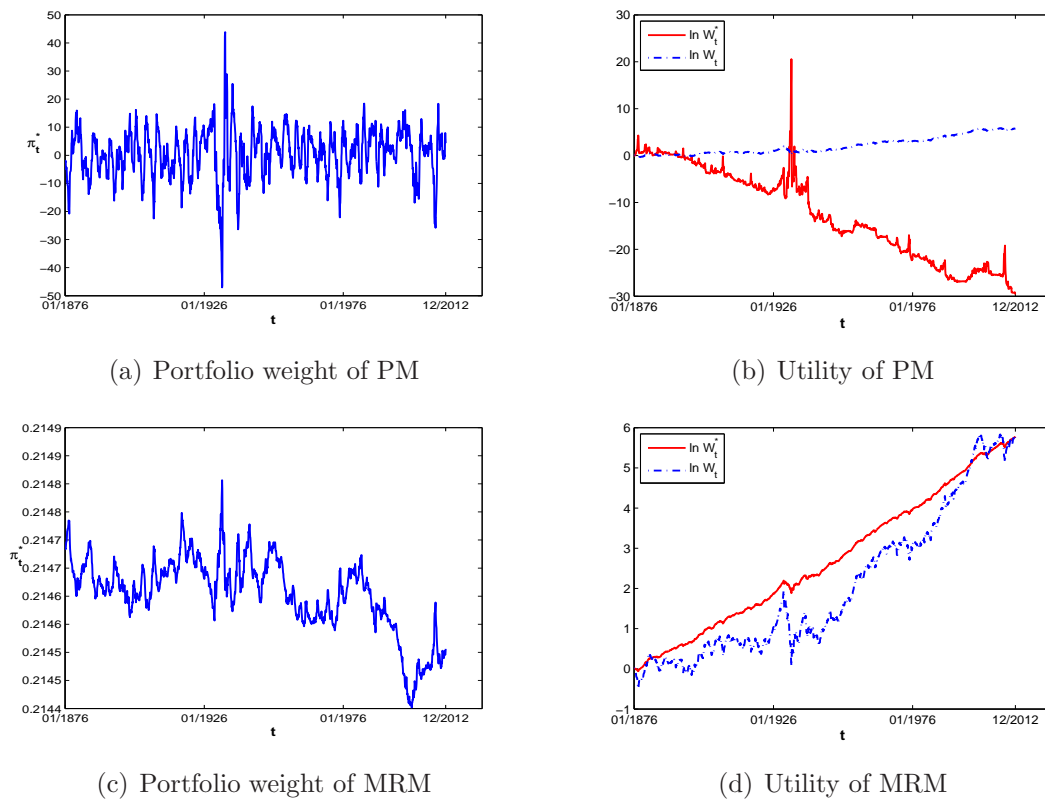


FIGURE 3.2. The time series of the optimal portfolio weight and the utility of the wealth for the pure momentum model with $\tau = 12$ (a) and (b) and the pure mean-reversion model (c) and (d) from January 1876 until December 2012.

Next, we compare the economic value of the pure momentum and pure mean-reverting strategies to that of the market index. For the pure momentum model, based on the estimated parameters in Table 3.1, Fig. 3.2 (a) and (b) illustrates the time series of the portfolio weights and the utilities of the optimal portfolio for the pure momentum model from January 1876 to December 2012. Compared to the

full model illustrated in Fig. 3.1, the leverage of the pure momentum strategies is much higher, as indicated by the higher level of π_t^* . The optimal strategies for the pure momentum model suffer from high risk and perform worse than the market and hence the optimal strategies of the full model. Similarly, based on the estimates in Table 3.1, Fig. 3.2 (c) and (d) illustrates the time series of the portfolio weight and the utility of the wealth of the optimal portfolio for the pure mean-reversion model from January 1876 to December 2012, showing that the performance of the strategy is about the same as the stock index but worse than the optimal strategies (2.8). Note that in this case there is not much variation in the portfolio weight and the optimal portfolio does not capture the timing opportunity of the market trend and market volatility. Therefore, both the pure momentum and pure mean-reversion strategies underperform the market and the optimal strategies of the full model.

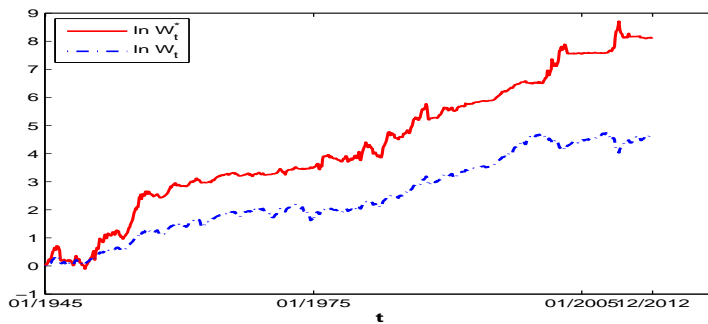


FIGURE 3.3. The time series of the utility of optimal portfolio wealth and that of the market index portfolio from January 1945 until December 2012.

There are two interesting observations from Fig. 3.1. First, the optimal strategies and index returns are positively correlated in general. In fact, the correlation is about 0.335. Second, Fig. 3.1 (d) seems to indicate that the improved utilities of the optimal portfolio wealth were mainly driven by the Great Depression in the 1930s. This observation is consistent with Moskowitz et al. (2012), who find that the TSM strategy delivers its highest profits during the most extreme market episodes. To clarify this observation, we also examine performance using data from January 1940 to December 2012 to avoid the Great Depression periods. We re-estimate the model, conduct the same analysis, and report the terminal utilities of the optimal portfolios in Fig. 3.3 over this time period. It shows that the optimal strategies still outperform the market index over this time period. This indicates that the outperformance of the optimal strategy is not necessarily due to extreme market episodes, such as the Great Depression. Later in this section, we show that the outperformance is in fact immune to market conditions.

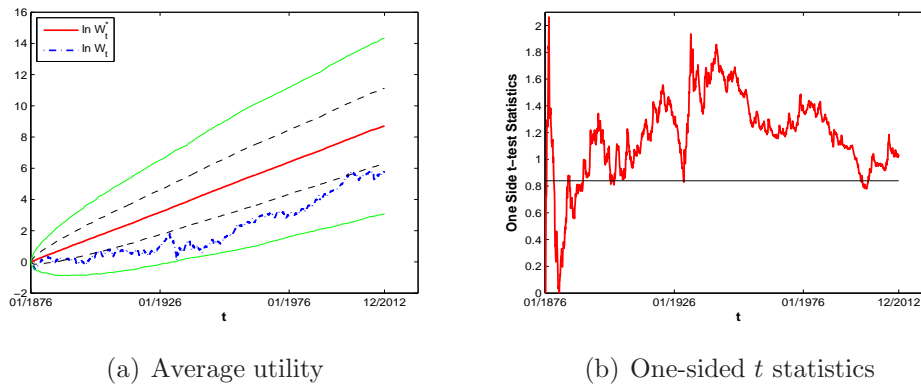


FIGURE 3.4. (a) Average utility and (b) one-sided t -test statistics based on 1,000 simulations for $\tau = 12$.

To provide further evidence for the economic value of the optimal strategy, we conduct a Monte Carlo analysis. For $\tau = 12$ and the estimated parameters, we simulate model (3.1) and report the average portfolio utilities (the solid red line in the middle) based on 1,000 simulations in Fig. 3.4 (a), together with 95% confidence levels (the two solid green lines outside), comparing to the utility of the market index (the dotted blue line). It shows that first, the average utilities of the optimal portfolios are better than that of the S&P 500. Second, the utility for the S&P 500 falls into the 95% confidence bounds and hence the average performance of the optimal strategy is not statistically different from the market index at the 95% confidence level. We also plot two black dashed bounds for the 60% confidence level. It shows that, at the 60% confidence level, the optimal portfolio significantly outperforms the market index. Fig. 3.4 (b) reports the one-sided t -test statistics to test $\ln W_t^* > \ln W_t^{SP500}$. The t -statistics are above 0.84 most of the time, which indicates a critical value at 80% confidence level. Therefore, with 80% confidence, the optimal portfolio significantly outperforms the market index. In summary, we have provided empirical evidence of the outperformance of the optimal strategy (2.8) compared to the market index, pure momentum and pure mean-reversion strategies.

3.3. The Sharpe Ratio. We now use the Sharpe ratio to examine the performance of the optimal strategy. The Sharpe ratio is defined as the ratio of the mean excess return on a portfolio and the standard deviation of the portfolio return. When the Sharpe ratio of an active strategy exceeds the market Sharpe ratio, we say that the active portfolio outperforms or dominates the market portfolio (in an unconditional mean-variance sense). For empirical applications, the (ex-post) Sharpe ratio is usually estimated as the ratio of the sample mean of the excess return on the portfolio and the sample standard deviation of the portfolio return (Marquering and Verbeek 2004). The average monthly return on the total return index of the S&P 500 over

the period January 1871–December 2012 is 0.42% with an estimated (unconditional) standard deviation of 4.11%. The Sharpe ratio of the market index is 0.021. For the optimal strategy (2.8), the return of the optimal portfolio wealth at time t is given by

$$R_t^* = (W_t^* - W_{t-1}^*)/W_{t-1}^* = \pi_{t-1}^* R_t + (1 - \pi_{t-1}^*) r. \quad (3.3)$$

Table 3.2 reports the Sharpe ratios of the passive holding market index portfolio and the optimal portfolios from January 1886 to December 2012 for $\tau = 12$ together with their 90% confidence intervals (see Jobson and Korkie 1981). It shows that, by taking the timing opportunity (with respect to the market trend and market volatility), the optimal portfolio outperforms the market. We also conduct a Monte Carlo analysis based on 1,000 simulations and obtain an average Sharpe ratio of 6.12% for the optimal portfolio. The result is consistent with the outperformance of the optimal portfolio measured by portfolio utility (with an average terminal utility of 8.71 for the optimal portfolio).

TABLE 3.2. The Sharpe ratios of the optimal portfolio and the market index with corresponding 90% confidence interval and the Sharpe ratio of the optimal portfolio based on Monte Carlo simulations.

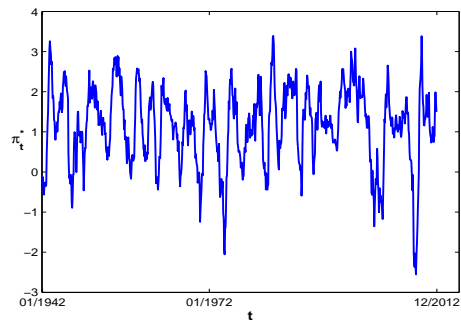
	Optimal portfolio	Market index	Monte Carlo
Sharpe ratio (%)	5.85	2.11	6.12
Bounds (%)	(1.86, 9.84)	(-1.88, 6.10)	(5.98, 6.27)

In summary, we have used two performance measures and provided empirical evidence of the outperformance of the optimal strategy (2.8) compared to the market index, pure momentum and pure mean-reversion strategies. The results provide empirical support for the analytical result on the optimal strategy derived in Section 2. In the following section, we conduct further empirical tests on these results. We first conduct out-of-sample tests on the predication power of the model and then examine the performance of the optimal strategy with short-sale constraints, market states, sentiment and volatility.

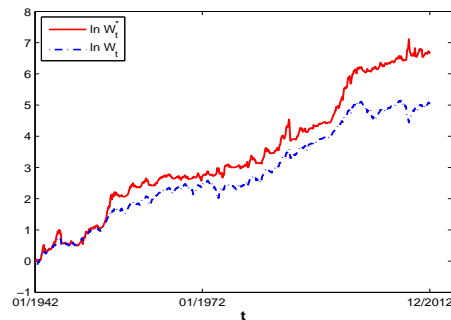
3.4. Out-of-Sample Tests. We implement a number of out-of-sample tests for the optimal strategies by splitting the whole data set into two sub-sample periods and using the first sample period to estimate the model. We then apply the estimated parameters to the second portion of the data to examine the out-of-sample performance of the optimal strategies.

In the first test, we split the whole data set into two equal periods: January 1871 to December 1941 and January 1942 to December 2012. Notice the data in the two periods are quite different; the market index increases gradually in the first period but fluctuates widely in the second period as illustrated in Fig. 3.1 (a). With $\tau = 12$,

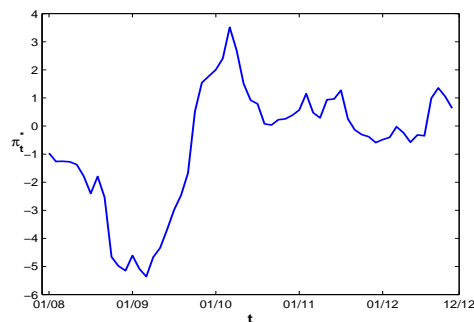
Fig. 3.5 (a) and (b) illustrates the corresponding time series of the optimal portfolio and the utility of the optimal portfolio wealth from January 1942 to December 2012, showing that the utility of the optimal strategy grows gradually and outperforms the market index.



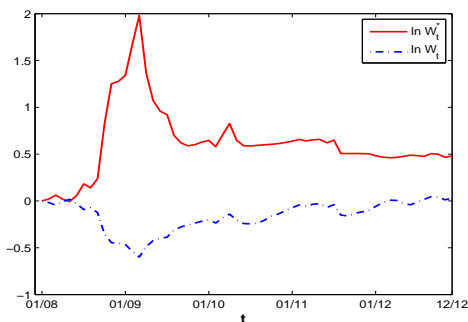
(a) The portfolio weight: 1/1942–12/2012



(b) The utility: 1/1942–12/2012



(c) The portfolio weight: 1/2008–12/2012



(d) The utility: 1/2008–12/2012

FIGURE 3.5. The time series of out-of-sample optimal portfolio weights and utility of the optimal portfolio wealth (the solid lines) from January 1942 until December 2012 in (a) and (b) and from January 2008 to December 2012 in (c) and (d) with $\tau = 12$ compared to the utility of the market index (the dotted line).

Many studies (see, for example, Jegadeesh and Titman 2011) show that momentum strategies perform poorly after the subprime crisis in 2008. In the second test, we use the subprime crisis to split the whole sample period into two periods and focus on the performance of the optimal strategies after the subprime crisis. The results are reported in Fig. 3.5 (c) and (d). It is clear that the optimal strategy still outperforms the market over the sub-sample period, in particular, during the financial crisis period around 2009 by taking large short positions in the optimal portfolios. We also use data from the last 10 years and 20 years as the out-of-sample test and find the results are robust.

As the third test, we implement the rolling window estimation procedure to avoid look-ahead bias. For $\tau = 12$, we estimate parameters at each month by using the past 20 years' data and report the results in Fig. C.1 in Appendix C. We then report the time series of the index level (a), the simple return of the total return index of S&P 500 (b), the optimal portfolio (c), and the utility of the optimal portfolio wealth (d) in Fig. C.2 of Appendix C, showing a strong performance of the optimal portfolios over the market.

We also implement the out-of-sample tests for the pure momentum and pure mean-reversion models (not reported here) and find that they cannot outperform the market in most out-of-sample tests (last 10, 20 and 71 years), but do outperform the market for out-of-sample tests over the last five years. We also report the results of out-of-sample tests of the pure momentum in Fig. C.4 and the pure mean reversion in Fig. C.6 based on the 20-year rolling window estimates in Fig. C.3 and Fig. C.5 respectively, in Appendix C. We also implement the estimations for different window sizes of 25, 30 and 50 years (not reported here) and find that the estimated parameters are insensitive to the size of rolling window and the performance of strategies is similar to the case of 20-year rolling window estimation. Overall, the out-of-sample tests demonstrate the robustness of the outperformance of the optimal trading strategies compared to the market index, pure momentum and pure mean-reversion strategies.

3.5. Short-sale Constraints and Transaction Costs. Investors often face short-sale constraints. To evaluate optimal strategies under such constraints, we consider them when short selling and borrowing (at the risk-free rate) are not allowed. The portfolio weight π in this case must lie between zero and 1. Since the value function is concave with respect to π , the optimal strategy becomes

$$\Pi_t^* = \begin{cases} 0, & \text{if } \pi_t^* < 0, \\ \pi_t^*, & \text{if } 0 \leq \pi_t^* \leq 1, \\ 1, & \text{if } \pi_t^* > 1. \end{cases} \quad (3.4)$$

TABLE 3.3. The terminal utility of the portfolio wealth, Sharpe ratio, mean and stand deviation of the portfolio weights for the optimal portfolios with and without short-sale constraints, comparing with the market index portfolio.

	Utility	Sharpe Ratio	Average weights	Std of weights
With constraints	10.35	0.12	0.43	0.46
Without constraints	17.06	0.06	0.23	1.74
Market index	5.76	0.02		

Table 3.3 reports the terminal utilities and the Sharpe ratio of the optimal portfolio with and without short-sale constraints, compared to the passive holding market index portfolio. It shows that, based on the two performance measures, the optimal portfolio with short-sale constraints outperforms both the market and the optimal portfolios without short-sale constraints. Therefore, constraints can improve performance. This observation is consistent with Marquering and Verbeek (2004 p. 419) who argue that “*While it may seem counterintuitive that strategies perform better after restrictions are imposed, it should be stressed that the unrestricted strategies are substantially more affected by estimation error.*” To support this argument, we also examine the mean and standard deviation of the optimal portfolio weights and report the results in Table 3.3 with and without short-sale constraints. It shows that, with the constraints, the mean of the optimal portfolio weights is high while the volatility is low. On the other hand, without constraints the mean of the optimal portfolio weights is low but the volatility is high, which seems in line with Marquering and Verbeek’s argument.

In addition, we examine the effect of transaction costs. With a transaction cost of 0.5% or 1%, we find little change in the terminal utilities and the Sharpe ratios.

3.6. Market States, Sentiment and Volatility. The cross-sectional momentum literature has shown that momentum profitability can be affected by market states, investor sentiment and market volatility. For example, Cooper, Gutierrez and Hameed (2004) find that short-run (six months) momentum strategies make profits in an up market and lose in a down market, but the up-market momentum profits reverse in the long run (13–60 months). Hou, Peng and Xiong (2009) find momentum strategies with a short time horizon (one year) are not profitable in a down market, but are profitable in an up market. Similar profitability results are also reported in Chordia and Shivakumar (2002), specifically that common macroeconomic variables related to the business cycle can explain positive returns to momentum strategies during expansionary periods and negative returns during recessions. Baker and Wurgler (2006, 2007) find that investor sentiment affects cross-sectional stock returns and the aggregate stock market. Wang and Xu (2012) find that market volatility has significant power to forecast momentum profitability. For TSMs, however, Moskowitz et al. (2012) find that there is no significant relationship of TSM profitability to either market volatility or investor sentiment.

To investigate the performance of optimal strategies under different market states, we follow Cooper et al. (2004) and Hou et al. (2009) and define market state using the cumulative return of the stock index (including dividends) over the most recent 36 months. We label a month as an up (down) market month if the three-year return of the market is non-negative (negative). We compute the average return of

the optimal strategy and compare the average returns between up and down market months. We see from Table D.1 in Appendix D that the unconditional average excess return is 87 basis points per month. In up months, the average excess return is 81 basis points and it is statistically significant. In down months, the average excess return is 101 basis points; this value is economically significant although it is not statistically significant. The difference between down and up months is 20 basis points, which is not significantly different from zero, based on a two-sample t -test (p -value of 0.87). We then implement the time series analysis by regressing the excess portfolio returns on a constant, an up-month dummy and the excess market return. We report the results in Table D.2 in Appendix D for the optimal strategy, the pure momentum strategy, pure mean-reversion strategy and the TSM strategy in Moskowitz et al. (2012) for $\tau = 12$ respectively. Except for the TSM, which earns significant positive returns in down markets, both constant term α and the coefficient of the up-month dummy κ are insignificant, indicating that the average return in down months and the incremental average return in up months are both insignificant for all other strategies; these results are consistent with those in Table D.1. The results are robust when we replace the up-month dummy with the lagged market return over the previous 36 months (not reported here). We also control for market risk in up and down months, with similar results. Simple predictive regression of excess portfolio returns on the up-month dummy indicates that the market state has no predictive power on portfolio returns. The results are also robust for the CAPM-adjusted return. Compared with the findings in Hou et al. (2009), where cross-sectional momentum returns are higher in up months, we do not find significant differences between up and down months for the strategies from our model and the TSM. Among these only the TSM shows significant returns in down months.

In terms of the effects of investor sentiment on portfolio performance, we regress the excess portfolio return on the previous month's sentiment index constructed by Baker and Wurgler (2006). We find (see Table D.6 in Appendix D) that investor sentiment has no predictive power on portfolio returns. We also examine the predictability of market volatility to the portfolio return. The time series analysis of regressing the excess portfolio return on the past month's volatility or on the past month's volatility conditional on up and down market state, suggests that market volatility has no predictive power on portfolio returns (see Tables D.7 and D.8 in Appendix D).

Overall, we find that returns of the optimal strategies are not significantly different in up and down market states. We also find that both investor sentiment and market volatility have no predictive power for the returns of the optimal strategies. In fact, the optimal strategies have taken these factors into account and hence the returns of

the optimal strategies have no significant relationship with these factors. Therefore, the optimal strategies are immune to market states, investor sentiment and market volatility.

3.7. Comparison with TSM. We now compare the performance of the optimal strategy to the TSM strategy of Moskowitz et al. (2012). The momentum strategies in the empirical studies are based on trading signals only. We first verify the profitability of the TSM strategies and then examine the excess return of buy-and-hold strategies when the position is determined by the sign of the optimal portfolio strategies (2.8) with different combinations of time horizons τ and holding periods h .

For a given look-back period τ , we take long/short positions based on the sign of the optimal portfolio (2.8). Then for a given holding period h , we calculate the monthly excess return of the strategy (τ, h) . Table E.1 in Appendix E reports the average monthly excess return (%) of the optimal strategies, skipping one month between the portfolio formation period and holding period to avoid the one-month reversal in stock returns, for different look-back periods (in the first column) and different holding periods (in the first row). The average return is calculated in the same way as in Moskowitz et al. (2012). We calculate the excess returns of the optimal strategies over the period from January 1881 (10 years after January 1871 with five years for calculating the trading signals and five years for holding periods) to December 2012.

For comparison, Table E.2 in Appendix E reports the average returns (%) for the pure momentum model.¹² Notice that Tables E.1 and E.2 indicate that strategy (9, 1) performs the best. This is consistent with the finding in Moskowitz et al. (2012) that strategy (9, 1) is the best strategy for equity markets although the 12-month horizon is the best for most asset classes.

TABLE 3.4. The Sharpe ratio of the optimal portfolio, market index, TSM and MMR for $\tau = 12$ with corresponding 90% confidence interval.

	Optimal portfolio	Market index	TSM	MMR
Sharpe ratio (%)	5.85	2.11	-0.03	4.16
Bounds (%)	(1.86, 9.84)	(-1.88, 6.10)	(-4.01, 3.96)	(0.18, 8.15)

Next we use the Sharpe ratio to examine the performance of the optimal strategy π_t^* of (2.8) and compare it to the passive index strategy and two TSM strategies: one follows from Moskowitz et al. (2012) and the other is the TSM strategy based on the

¹²Notice the position is completely determined by the sign of the optimal strategies. Therefore, the position used in Table E.2 is the same as that of the TSM strategies in Moskowitz et al. (2012).

sign of the optimal strategies $sign(\pi_t^*)$ as the trading signal (instead of the average excess return over a past period), which is called *momentum and mean-reversion (MMR) strategy* for convenience. For a time horizon of $\tau = 12$ months, we report the Sharpe ratios of the portfolios for the four strategies in Table 3.4 from January 1881 to December 2012. It shows that the TSM strategy underperforms the market while the MMR strategy outperforms it. The optimal strategy also significantly outperforms all the momentum, mean-reversion and TSM strategies. Note that the only difference between the optimal strategy and the MMR strategy is that the former considers the size of the portfolio position, which is inversely proportional to the variance, while the latter always takes one unit of long/short position. This implies that, in addition to trends, the size of the position is another very important factor for investment profitability.

Following Moskowitz et al. (2012), we examine the cumulative excess return. That is, the return at time t is defined by

$$\hat{R}_{t+1} = sign(\pi_t^*) \frac{0.1424}{\hat{\sigma}_{S,t}} R_{t+1}, \quad (3.5)$$

where 0.1424 is the sample standard deviation of the total return index and the ex-ante annualized variance $\hat{\sigma}_{S,t}^2$ for the total return index is calculated as the exponentially weighted lagged squared month returns,

$$\hat{\sigma}_{S,t}^2 = 12 \sum_{i=0}^{\infty} (1 - \delta) \delta^i (R_{t-1-i} - \bar{R}_t)^2, \quad (3.6)$$

here the constant 12 scales the variance to be annual, and \bar{R}_t is the exponentially weighted average return based on the weights $(1 - \delta) \delta^i$. The parameter δ is chosen so that the center of mass of the weights is $\sum_{i=1}^{\infty} (1 - \delta) \delta^i = \delta / (1 - \delta) =$ two months. To avoid look-ahead bias contaminating the results, we use the volatility estimates at time t for time $t + 1$ returns throughout the analysis.

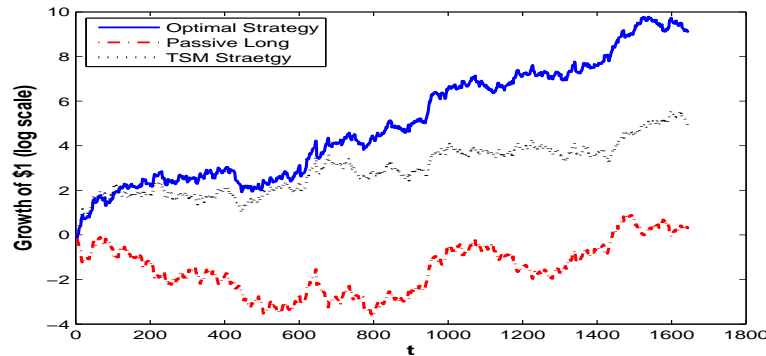


FIGURE 3.6. Log cumulative excess return of the optimal strategy and momentum strategy with $\tau = 12$ and passive long strategy from January 1876 to December 2012.

With a 12-month time horizon Fig. 3.6 illustrates the log cumulative excess return of the optimal strategy (2.8), the momentum strategy and the passive long strategy from January 1876 to December 2012. It shows that the optimal strategy has the highest growth rate and the passive long strategy has the lowest growth rate. The pattern of Fig. 3 in Moskowitz et al. (2012 p.239) is replicated in Fig. 3.6, showing that the TSM strategy outperforms the passive long strategy.¹³ In summary, we have shown that the optimal strategy outperforms the TSM strategy of Moskowitz et al. (2012). By comparing the performance of two TSM strategies, we find that the TSM strategy based on momentum and reversal trading signal is more profitable than the pure TSM strategy of Moskowitz et al. (2012).¹⁴

4. TIME HORIZON EFFECTS

The results in the previous section are based on a time horizon of $\tau = 12$ months. In this section, we examine the effect of a time horizon τ varying from one to 60 months on the outperformance of the optimal strategies. The impact of time horizon on investment profitability has been extensively investigated in the empirical literature, for example, De Bondt and Thaler (1985) and Jegadeesh and Titman

¹³ In fact, the profits of the diversified time series momentum (TSMOM) portfolio in Moskowitz et al. (2012) are to some extent driven by the bonds when scaling for the volatility in equation (5) of their paper, and hence applying the TSM strategies to the stock index may have fewer significant profits than the diversified TSMOM portfolio.

¹⁴ This paper studies the S&P 500 index over 140 years of data, while Moskowitz et al. (2012) focus on the futures and forward contracts that include country equity indexes, currencies, commodities, and sovereign bonds. Despite a large difference between the data investigated, we find similar patterns for the TSM in the stock index and replicate their results with respect to the stock index.

(1993). Because of the closed-form optimal strategy (2.8), we are able to explicitly examine the dependence of the optimal results on different time horizons.

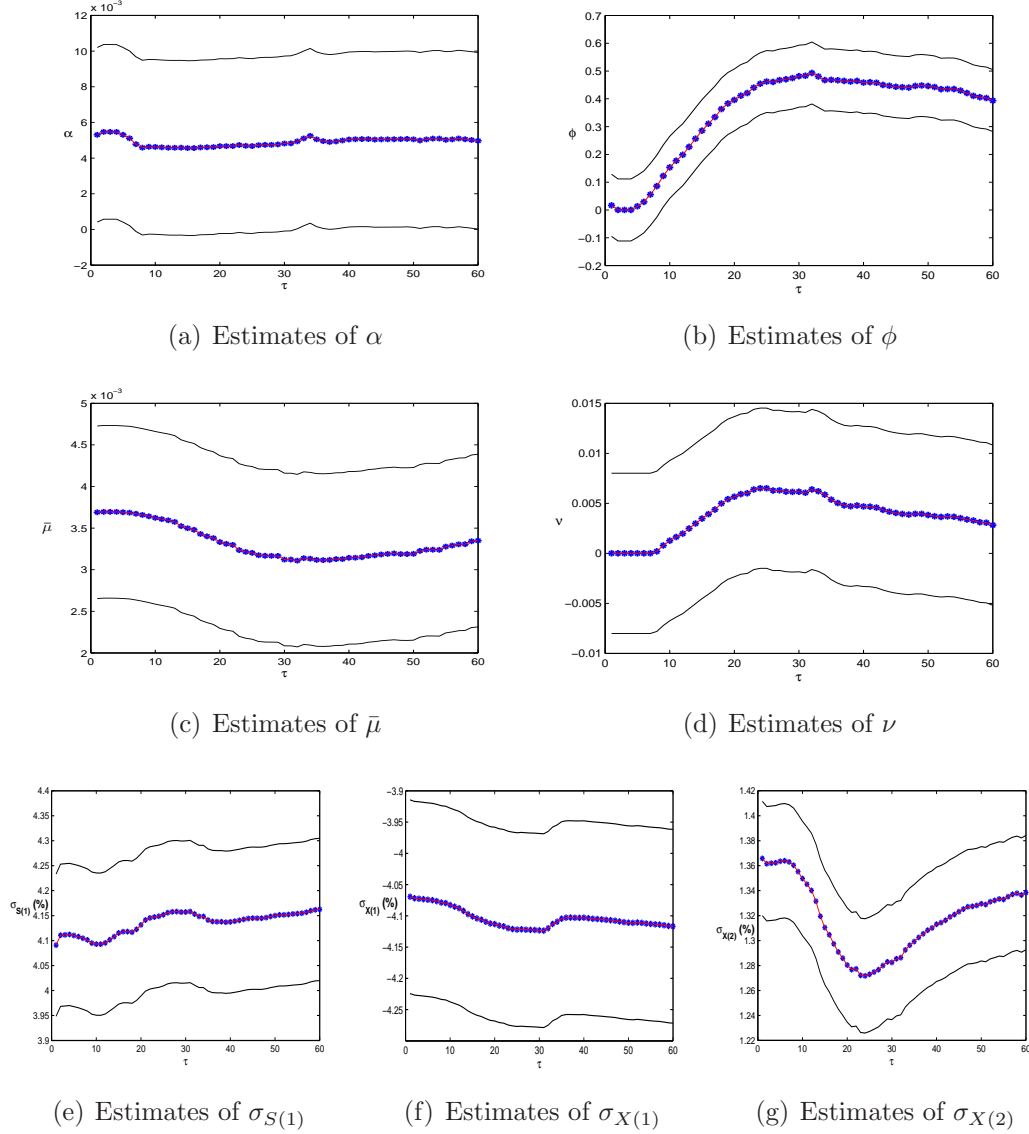


FIGURE 4.1. The estimates of (a) α ; (b) ϕ ; (c) $\bar{\mu}$; (d) ν ; (e) $\sigma_{S(1)}$; (f) $\sigma_{X(1)}$ and (g) $\sigma_{X(2)}$ as functions of τ .

4.1. Model Estimations and Comparison. The estimations are conducted separately for given a time horizon τ . Fig. 4.1 reports the estimated parameters in monthly terms for τ ranging from one month to five years, together with the 95% confidence bounds. Fig. 4.1 (b) shows that the momentum effect parameter ϕ is

significantly different from zero when time horizon τ is more than half a year, indicating a significant momentum effect for τ beyond six months.¹⁵ Note that ϕ increases to about 50% when τ increases from six months to three years and then decreases gradually when τ increases further. This implies that market returns can be explained by both the momentum (based on different time horizons) and mean-reverting components. Other results in terms of the level and significance reported in Fig. 4.1 are consistent with Koijsen et al. (2009).

Obviously, the estimations depend on the specification of the time horizon τ . To explore the optimal value for τ , we compare different information criteria, including Akaike (AIC), Bayesian (BIC) and Hannan–Quinn (HQ) information criteria for τ from one month to 60 months in Fig. F.1 of Appendix F. The results imply that the average returns over the past 18 months to two years can best predict future returns and the explanatory power for the market returns is reduced for longer time horizons. This is consistent with studies showing that short-term (one to two years), rather than long-term, momentum better explains market returns. Combining the results in Figs 4.1 (b) and F.1, we can conclude that market returns are better captured by short-term momentum and long-term reversion.

To compare the performance of the optimal strategies with the pure momentum strategies for different τ , we estimate the model with $\phi = 1$. For the pure momentum model ($\phi = 1$), there is only one parameter $\sigma_{S(1)}$ to be estimated. Fig. F.2 (a) reports the estimates of $\sigma_{S(1)}$ and the 95% confidence bounds for $\tau \in [1, 60]$. It shows that as τ increases, the volatility of the index decreases dramatically for small time horizons and is then stabilized for large time horizons. It implies high volatility associated with momentum over short time horizons and low volatility over long time horizons. We also compare the information criteria for different τ (not reported here) and find that all the AIC, BIC and HQ reach their minima at $\tau = 11$. This implies that the average returns over the previous 11 months can predict future returns best for the pure momentum model. This is consistent with the finding of Moskowitz et al. (2012) that momentum returns over the previous 12 months better predict the next month's return than other time horizons. In addition, we conduct the log-likelihood ratio test to compare the full model to the pure momentum model ($\phi = 1$) and to the pure mean-reversion model for different τ . We report the log-likelihood ratio test results in Fig. F.2 (b), which show that the full model is significantly better than the pure momentum model and pure mean-reversion model for all τ .

¹⁵ For τ from one to five months, ϕ is indifferent from zero statistically and economically. Correspondingly, for small look-back periods of up to half a year, the model is equivalent to a pure mean-reversion model. This observation is helpful when explaining the results of the model for small look-back periods in the following discussion.

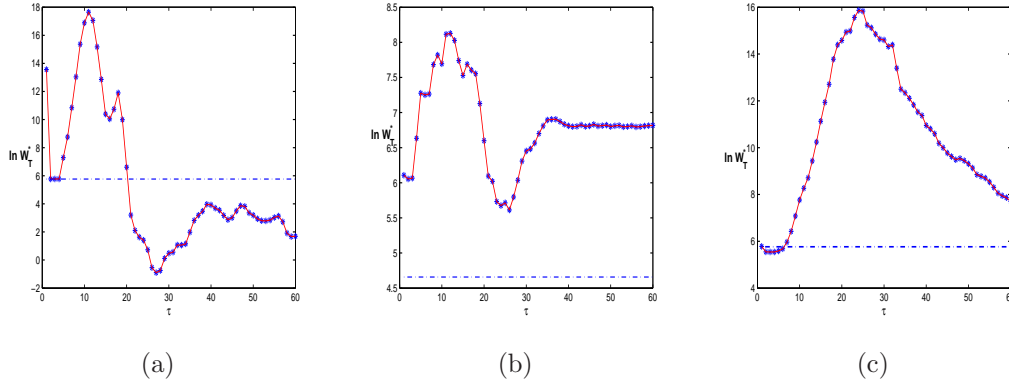


FIGURE 4.2. The terminal utility of the optimal portfolio wealth (a) from January 1876 to December 2012, (b) from January 1945 to December 2012, and (c) the average terminal utility of the optimal portfolios based on 1000 simulations from January 1876 to December 2012, comparing with the terminal utility of the market index portfolio (the dash-dotted line).

4.2. The effect on performance. For $\tau = 1, 2, \dots, 60$, based on the estimations of the full model over the full sample, Fig. 4.2 (a) reports the utility of terminal wealth, compared to the utility of the market portfolio at December 2012. It shows that the optimal strategies consistently outperform the market index for τ from five to 20 months.¹⁶ The corresponding utilities are plotted in Fig. F.4.

We observed from Fig. 3.1 (d) for $\tau = 12$ that the improved terminal utilities of the optimal portfolio wealth might be driven by the Great Depression in the 1930s. To clarify this observation, we also examine performance using the data from January 1940 to December 2012 to avoid the Great Depression period. We re-estimate the model, conduct the same analysis, and report the terminal utilities of the optimal portfolios in Fig. 4.2 (b) over this time period. It shows that the optimal strategies still outperform the market and the performance of the optimal strategies over the more recent time period becomes even better for all time horizons. Consistent with the results obtained in the previous section, the outperformance of the optimal strategy is not necessarily due to extreme market episodes, such as the Great Depression.

¹⁶When τ is less than half a year, Fig. 4.2 (a) shows that the optimal strategies do not perform significantly better than the market. As we indicate in footnote 15, the model with a small look-back period of up to half a year performs similarly to the pure mean-reversion strategy. Note the significant outperformance of the optimal strategy with a one-month horizon in Fig. 4.2 (a). This is due to the fact that the first order autocorrelation of the return of the S&P 500 is significantly positive ($AC(1) = 0.2839$) while the autocorrelations with higher orders are insignificantly different from zero. This implies that the last period return could well predict the next period return.

We also conduct further Monte Carlo analysis on the performance of the optimal portfolios based on the estimated parameters in Fig. 4.1 and 1,000 simulations and report the average terminal utilities in Fig. 4.2 (c). The result displays a different terminal performance from that in Fig. 4.2 (a). In fact, the terminal utility in Fig. 4.2 (a) is based on only one specific trajectory (the real market index), while Fig. 4.2 (c) provides the average performance based on 1,000 trajectories. We find that the optimal portfolios perform significantly better than the market index (the dash-dotted constant level) for all time horizons beyond half a year. In particular, the average terminal utility reaches its peak at $\tau = 24$, which is consistent with the result based on the information criteria in Fig. F.1, particularly the AIC. Therefore, according to the utility of portfolio wealth, the optimal strategies outperform the market index for most of the time horizons.

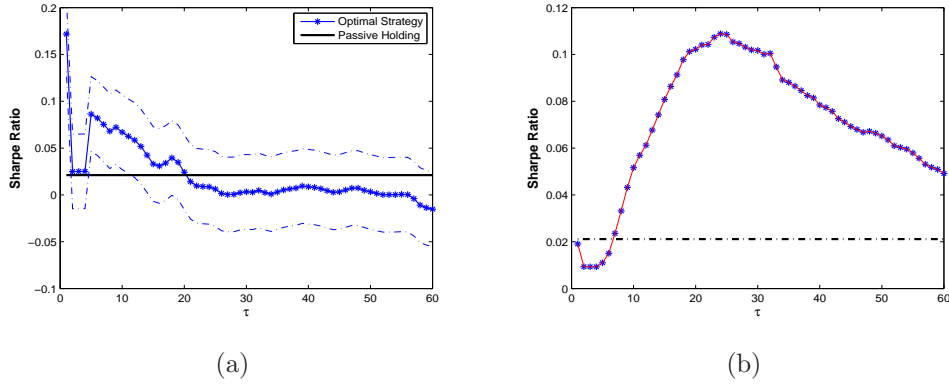


FIGURE 4.3. The Sharpe ratio of the optimal portfolio (the solid blue line) with corresponding 90% confidence intervals (a), the average Sharpe ratio based on 1,000 simulations (b) for $\tau \in [1, 60]$, compared to the passive holding portfolio of market index (the dotted black line) from January 1881 to December 2012.

As the second performance measure, Fig. 4.3 (a) reports the Sharpe ratio of the passive holding market index portfolio from January 1881 to December 2012 and the Sharpe ratios of the optimal portfolios for τ from one month to 60 months together with their 90% confidence intervals (see Jobson and Korkie 1981). If we consider the optimal portfolio as a combination of the market portfolio and a risk-free asset, then the optimal portfolio should be located on the capital market line and hence should have the same Sharpe ratio as the market. However Fig. 4.3 (a) shows that, by taking the timing opportunity (with respect to the market trend and market volatility), the optimal portfolios (the dotted blue line) outperform the market (the solid black line) on average for time horizons from six to 20 months. The results are surprisingly consistent with that in Fig. 4.2 (a) under the utility measure. We also

conduct a Monte Carlo analysis based on 1,000 simulations and report the average Sharpe ratios in Fig. 4.3 (b) for the optimal portfolios. It shows the outperformance of the optimal portfolios over the market index based on the Sharpe ratio for the look-back periods of more than six months. The results are consistent with that in Fig. 4.2 (c) under the portfolio utility measure. In addition, we show in Fig. F.3 that the pure momentum strategies underperform the market in all time horizons from one month to 60 months. Therefore, we have demonstrated the consistent outperformance of the optimal portfolios over the market index and pure strategies under the two performance measures.

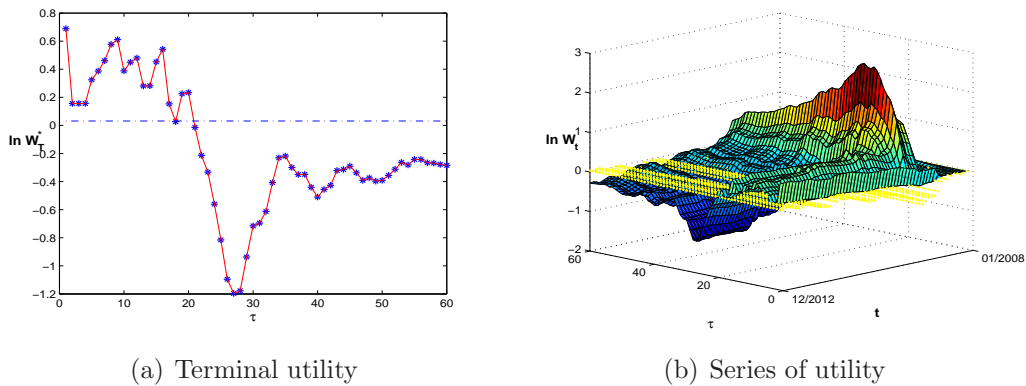


FIGURE 4.4. The terminal utility of the wealth for the optimal portfolio, compared to the passive holding market index portfolio (the dotted line), with out-of-sample data from January 2008 to December 2012 for $\tau \in [1, 60]$.

4.3. The effect on the out-of-sample tests. For τ from one month to 60 months, Fig. 4.4 reports the out-of-sample utility of the optimal portfolio wealth from January 2008 to December 2012. It clearly shows that the optimal strategies still outperform the market index for time horizons up to two years. We report additional out-of-sample tests in Appendix F.4 and rolling window estimates in Appendix F.5.

4.4. The effect on short-sale constraints. For different time horizon, Fig. 4.5 (a) and (b) report the terminal utilities of the optimal portfolio wealth and the Sharpe ratio for the optimal portfolio with and without short-sales constraints, respectively, comparing with the passive holding market index portfolio. We also examine the mean and standard deviation of the optimal portfolio weights and report the results in Fig. 4.5 (c) and (d) with and without short-sale constraints. The results for $\tau = 12$ in the previous section also hold. That is, with the constraints, the optimal portfolio weights increase in the mean while volatility is low and stable. On the other hand, without constraints, the volatility of the optimal portfolio

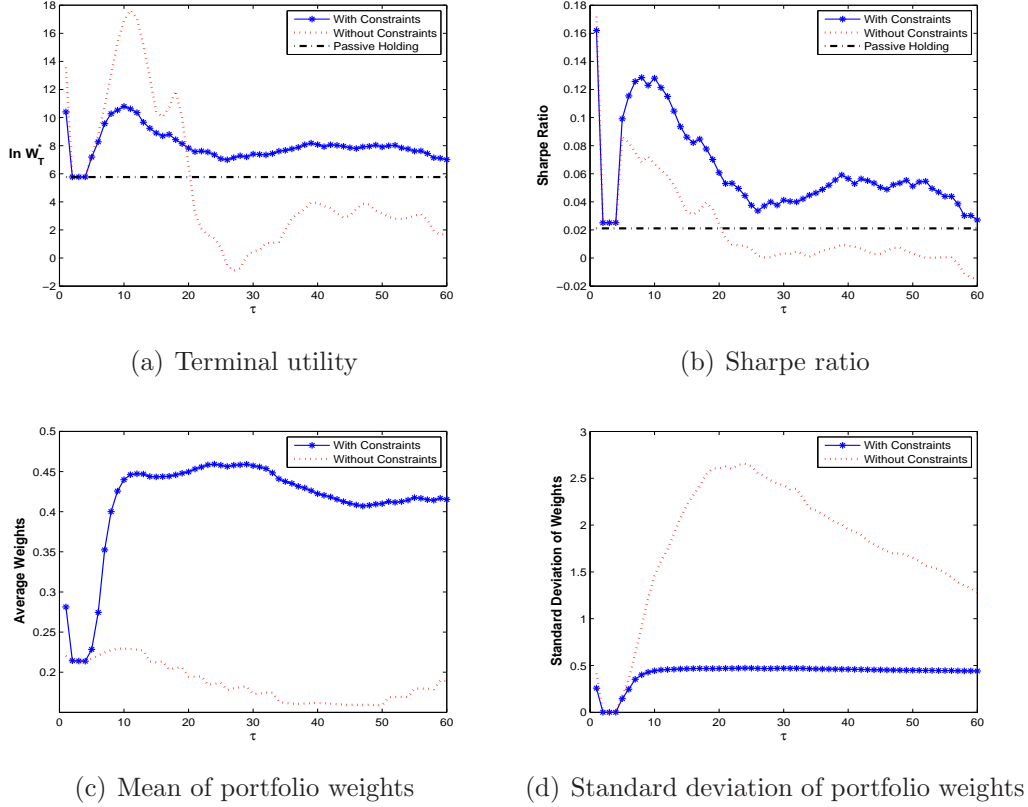


FIGURE 4.5. The terminal utility of wealth (a) and the Sharpe ratio (b) for the optimal portfolio, the mean (c) and the standard deviation of the optimal portfolio weights, with and without short-sale constraints, compared with the market index portfolio.

weights varies dramatically, which seems in line with the argument of Marquering and Verbeek (2004).

4.5. Comparison with TSM with different time horizons. As in the previous section for $\tau = 12$, we use the Sharpe ratio to examine the performance of the optimal strategy π_t^* in (2.8) and compare with the passive index strategy and two TSM strategies for time horizons from 1 month to 60 months and one month holding period. We report the Sharpe ratios of the portfolios for the four strategies in Fig. 4.6 (a).¹⁷ For comparison, we collect the Sharpe ratio for the optimal portfolio and the passive holding portfolio reported in Fig. 4.3 and report the Sharpe ratios of the TSM strategy using a solid green line and of momentum and mean-reversion strategy using a dotted red line together in Fig. 4.6 (a) from January 1881 to December 2012. We have three observations. First, the TSM strategy outperforms

¹⁷The monthly Sharpe ratio for the pure mean-reversion strategy is 0.0250, slightly higher than that for the passive holding portfolio (0.0211).

the market only for $\tau = 9, 10$ and the momentum and mean-reversion strategy outperform the market for short time horizons $\tau \leq 13$. Second, by taking the mean-reversion effect into account, the momentum and mean-reversion strategy performs better than the TSM strategy for all time horizons. Finally, the optimal strategy significantly outperforms both the momentum and mean-reversion strategy (for all time horizons beyond four months) and the TSM strategy (for all time horizons).

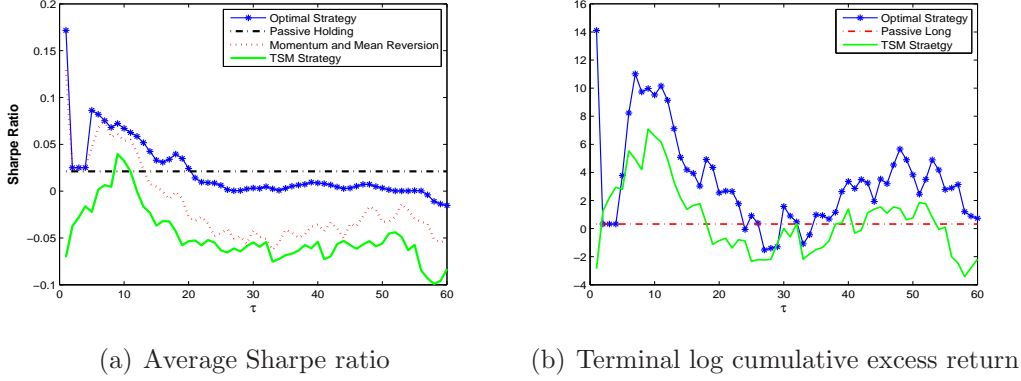


FIGURE 4.6. (a) The average Sharpe ratio for the optimal portfolio, the momentum and mean-reversion portfolio and the TSM portfolio with $\tau \in [1, 60]$ and the passive holding portfolio from January 1881 until December 2012. (b) Terminal log cumulative excess return of the optimal strategies and TSM strategies with $\tau \in [1, 60]$ and passive long strategy from January 1876 to December 2012.

Fig. 4.6 (b) shows the terminal values of the log cumulative excess returns of the optimal strategy (2.8) and the TSM strategy with $\tau \in [1, 60]$, together with the passive long strategy, from January 1876 to December 2012.¹⁸ It shows that the optimal strategy outperforms the TSM strategy for all time horizons (beyond four months), while the TSM strategy outperforms the market for small time horizons (from about two to 18 months). The terminal values of the log cumulative excess return have similar patterns to the average Sharpe ratio reported in Fig. 4.6 (a), especially for small time horizons.

¹⁸Note that the passive long strategy introduced in Moskowitz et al. (2012) is different from the passive holding strategy studied in the previous sections. Passive long means holding one share of the index each period; however, passive holding in our paper means investing \$1 in the index in the first period and holding it until the last period.

5. CONCLUSION

To characterize the time series momentum in financial markets, we propose a continuous-time model of asset price dynamics with the drift as a weighted average of mean reversion and moving average components. By applying the maximum principle for control problems of stochastic delay differential equations, we derive the optimal strategies in closed form. By estimating the model to the S&P 500, we show that the optimal strategy outperforms the TSM strategy and the market index. The outperformance holds for out-of-sample tests and with short-sale constraints. The outperformance is immune to the market states, investor sentiment and market volatility. The results show that the profitability pattern reflected by the average return of commonly used strategies in much of the empirical literature may not reflect the effect of portfolio wealth.

The model proposed in this paper is simple and stylized. The weights of the momentum and mean-reversion components are constant. When market conditions change, the weights can be time-varying. Hence it would be interesting to model their dependence on market conditions. This can be modelled, for example, as a Markov switching process or based on some rational learning process (Xia 2001). The portfolio performance is examined under log utility in this paper. It would be interesting to study the intertemporal effect under general power utility functions. We could also consider incorporating stochastic volatilities of the return process into the model. Finally, an extension of the model to a multi-asset setting to study cross-sectional optimal strategies would be helpful to understand cross-sectional momentum and reversal.

APPENDIX A. PROPERTIES OF THE SOLUTIONS TO THE SYSTEM (2.2)–(2.4)

Let $C([-\tau, 0], R)$ be the space of all continuous functions $\varphi : [-\tau, 0] \rightarrow R$. For a given initial condition $S_t = \varphi_t$, $t \in [-\tau, 0]$ and $\mu_0 = \hat{\mu}$, the following proposition shows that the system (2.2)–(2.4) admits pathwise unique solutions such that $S_t > 0$ almost surely for all $t \geq 0$ whenever $\varphi_t > 0$ for $t \in [-\tau, 0]$ almost surely.

Proposition A.1. *The system (2.2)–(2.4) has an almost surely continuously adapted pathwise unique solution (S, μ) for a given \mathcal{F}_0 -measurable initial process $\varphi : \Omega \rightarrow C([-\tau, 0], R)$. Furthermore, if $\varphi_t > 0$ for $t \in [-\tau, 0]$ almost surely, then $S_t > 0$ for all $t \geq 0$ almost surely.*

Proof. Basically, the solution can be found by using forward induction steps of length τ as in Arriojas, Hu, Mohammed and Pap (2007). Let $t \in [0, \tau]$. Then the system (2.2)–(2.4) becomes

$$\begin{cases} dS_t = S_t dN_t, & t \in [0, \tau], \\ d\mu_t = \alpha(\bar{\mu} - \mu_t)dt + \sigma'_\mu dZ_t, & t \in [0, \tau], \\ S_t = \varphi_t \text{ for } t \in [-\tau, 0] \text{ almost surely and } \mu_0 = \hat{\mu}. \end{cases} \quad (\text{A.1})$$

where $N_t = \int_0^t \left[\frac{\phi}{\tau} \int_{s-\tau}^s \frac{d\varphi_u}{\varphi_u} + (1 - \phi)\mu_s \right] ds + \int_0^t \sigma'_S dZ_s$ is a semimartingale. Denote by $\langle N_t, N_t \rangle = \int_0^t \sigma'_S \sigma_S ds$, $t \in [0, \tau]$, the quadratic variation. Then system (A.1) has a unique solution

$$\begin{cases} S_t = \varphi_0 \exp \left\{ N_t - \frac{1}{2} \langle N_t, N_t \rangle \right\}, \\ \mu_t = \bar{\mu} + (\hat{\mu} - \bar{\mu}) \exp\{-\alpha t\} + \sigma'_\mu \exp\{-\alpha t\} \int_0^t \exp\{\alpha u\} dZ_u \end{cases}$$

for $t \in [0, \tau]$. This clearly implies that $S_t > 0$ for all $t \in [0, \tau]$ almost surely, when $\varphi_t > 0$ for $t \in [-\tau, 0]$ almost surely. By a similar argument, it follows that $S_t > 0$ for all $t \in [\tau, 2\tau]$ almost surely. Therefore $S_t > 0$ for all $t \geq 0$ almost surely, by induction. Note that the above argument also gives existence and pathwise-uniqueness of the solution to the system (2.2)–(2.4). \square

APPENDIX B. PROOF OF PROPOSITION 2.1

To solve the stochastic control problems, there are two approaches: the dynamic programming method (HJB equation) and the maximum principle. Since the SDDE is not Markovian, we cannot use the dynamic programming method. Recently, Chen and Wu (2010) introduced a maximum principle for the optimal control problem of

SDDE. This method is further extended by Øksendal et al. (2011) to consider a one-dimensional system allowing both delays of moving average type and jumps. Because the optimal control problem of SDDE is relatively new to the field of economics and finance, we first briefly introduce the maximum principle of Chen and Wu (2010) and refer readers to their paper for details.

B.1. The Maximum Principle for an Optimal Control Problem of SDDE.

Consider a past-dependent state X_t of a control system

$$\begin{cases} dX_t = b(t, X_t, X_{t-\tau}, v_t, v_{t-\tau})dt + \sigma(t, X_t, X_{t-\tau}, v_t, v_{t-\tau})dZ_t, & t \in [0, T], \\ X_t = \xi_t, & v_t = \eta_t, & t \in [-\tau, 0], \end{cases} \quad (\text{B.1})$$

where Z_t is a d -dimensional Brownian motion on $(\Omega, \mathcal{F}, P, \{\mathcal{F}_t\}_{t \geq 0})$, and $b : [0, T] \times \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^k \times \mathbb{R}^k \rightarrow \mathbb{R}^n$ and $\sigma : [0, T] \times \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^k \times \mathbb{R}^k \rightarrow \mathbb{R}^{n \times d}$ are given functions. In addition, v_t is a \mathcal{F}_t ($t \geq 0$)-measurable stochastic control with values in U , where $U \subset \mathbb{R}^k$ is a nonempty convex set, $\tau > 0$ is a given finite time delay, $\xi \in C[-\tau, 0]$ is the initial path of X , and η , the initial path of $v(\cdot)$, is a given deterministic continuous function from $[-\tau, 0]$ into U such that $\int_{-\tau}^0 \eta_s^2 ds < +\infty$. The problem is to find the optimal control $u(\cdot) \in \mathcal{A}$, such that

$$J(u(\cdot)) = \sup\{J(v(\cdot)); v(\cdot) \in \mathcal{A}\}, \quad (\text{B.2})$$

where \mathcal{A} denotes the set of all admissible controls. The associated performance function J is given by

$$J(v(\cdot)) = \mathbb{E} \left[\int_0^T L(t, X_t, v_t, v_{t-\tau}) dt + \Phi(X_T) \right],$$

where $L : [0, T] \times \mathbb{R}^n \times \mathbb{R}^k \times \mathbb{R}^k \rightarrow \mathbb{R}$ and $\Phi : \mathbb{R}^n \rightarrow \mathbb{R}$ are given functions. Assume **(H1)**: the functions b , σ , L and Φ are continuously differentiable with respect to $(X_t, X_{t-\tau}, v_t, v_{t-\tau})$ and their derivatives are bounded.

In order to derive the maximum principle, we introduce the following adjoint equation,

$$\begin{cases} -dp_t = \{ (b_X^u)^\top p_t + (\sigma_X^u)^\top z_t + \mathbb{E}_t[(b_{X_\tau}^u|_{t+\tau})^\top p_{t+\tau} + (\sigma_{X_\tau}^u|_{t+\tau})^\top z_{t+\tau}] \\ \quad + L_X(t, X_t, v_t, v_{t-\tau}) \} dt - z_t dZ_t, & t \in [0, T], \\ p_T = \Phi_X(X_T), & p_t = 0, & t \in (T, T + \tau], \\ z_t = 0, & t \in [T, T + \tau]. \end{cases} \quad (\text{B.3})$$

We refer readers to Theorems 2.1 and 2.2 in Chen and Wu (2010) for the existence and uniqueness of the solutions of the systems (B.3) and (B.1) respectively.

Next, define a Hamiltonian function H from $[0, T] \times \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^k \times \mathbb{R}^k \times L^2_{\mathcal{F}}(0, T + \tau; \mathbb{R}^n) \times L^2_{\mathcal{F}}(0, T + \tau; \mathbb{R}^{n \times d})$ to \mathbb{R} as follows,

$$\begin{aligned} & H(t, X_t, X_{t-\tau}, v_t, v_{t-\tau}, p_t, z_t) \\ &= \langle b(t, X_t, X_{t-\tau}, v_t, v_{t-\tau}), p_t \rangle + \langle \sigma(t, X_t, X_{t-\tau}, v_t, v_{t-\tau}), z_t \rangle + L(t, X_t, v_t, v_{t-\tau}). \end{aligned}$$

Assume **(H2)**: the functions $H(t, \cdot, \cdot, \cdot, \cdot, p_t, z_t)$ and $\Phi(\cdot)$ are concave with respect to the corresponding variables respectively for $t \in [0, T]$ and given p_t and z_t . Then we have the following proposition on the maximum principle of the stochastic control system with delay by summarizing Theorem 3.1, Remark 3.4 and Theorem 3.2 in Chen and Wu (2010).

Proposition B.1. (i) *Let $u(\cdot)$ be an optimal control of the optimal stochastic control problem with delay subject to (B.1) and (B.2), and $X(\cdot)$ be the corresponding optimal trajectory. Then we have*

$$\max_{v \in U} \langle H_v^u + \mathbb{E}_t[H_{v_\tau}^u |_{t+\tau}], v \rangle = \langle H_v^u + \mathbb{E}_t[H_{v_\tau}^u |_{t+\tau}], u_t \rangle, \quad a.e., a.s.; \quad (\text{B.4})$$

(ii) *Suppose $u(\cdot) \in \mathcal{A}$ and let $X(\cdot)$ be the corresponding trajectory, p_t and z_t be the solution of the adjoint equation (B.3). If **(H1)**, **(H2)** and (B.4) hold for $u(\cdot)$, then $u(\cdot)$ is an optimal control for the stochastic delayed optimal problem (B.1) and (B.2).*

B.2. Proof of Proposition 2.1. We now apply Proposition B.1 to our stochastic control problem. Let $P_u := \ln S_u$ and $V_u := \ln W_u$. Then the stochastic delayed optimal problem in Section 2 becomes to maximize $\mathbb{E}_u[\Phi(X_T)] := \mathbb{E}_u[\ln W_T] = \mathbb{E}_u[V_T]$, subject to

$$\begin{cases} dX_u = b(u, X_u, X_{u-\tau}, \pi_u)du + \sigma(u, X_u, \pi_u)dZ_u, & u \in [t, T], \\ X_u = \xi_u, \quad v_u = \eta_u, & u \in [t - \tau, t], \end{cases} \quad (\text{B.5})$$

where

$$\begin{aligned} X_u &= \begin{pmatrix} P_u \\ \mu_u \\ V_u \end{pmatrix}, \quad \sigma = \begin{pmatrix} \sigma'_S \\ \sigma'_\mu \\ \pi_u \sigma'_S \end{pmatrix}, \\ b &= \begin{pmatrix} \frac{\phi}{\tau}(P_u - P_{u-\tau}) + (1 - \phi)\mu_u - (1 - \phi)\frac{\sigma'_S \sigma_S}{2} \\ \alpha(\bar{\mu} - \mu_u) \\ -\frac{\pi_u^2 \sigma'_S \sigma_S}{2} + \pi_u \left[\frac{\phi}{\tau}(P_u - P_{u-\tau}) + \frac{\sigma'_S \sigma_S}{2} \phi + (1 - \phi)\mu_u - r \right] + r \end{pmatrix}. \end{aligned}$$

Then we have the following adjoint equation

$$\begin{cases} -dp_u = \{ (b_X^{\pi^*})^\top p_u + (\sigma_X^{\pi^*})^\top z_u + \mathbb{E}_u[(b_{X_\tau}^{\pi^*}|_{u+\tau})^\top p_{u+\tau} + (\sigma_{X_\tau}^{\pi^*}|_{u+\tau})^\top z_{u+\tau}] \\ \quad + L_X \} du - z_u dZ_u, \quad u \in [t, T], \\ p_T = \Phi_X(X_T), \quad p_u = 0, \quad u \in (T, T + \tau], \\ z_u = 0, \quad u \in [T, T + \tau], \end{cases} \quad (\text{B.6})$$

where

$$\begin{aligned} p_u &= (p_u^i)_{3 \times 1}, \quad z_u = (z_u^{ij})_{3 \times 2}, \quad (b_X^{\pi^*})^\top = \begin{pmatrix} \frac{\phi}{\tau} & 0 & \frac{\phi}{\tau} \pi_u^* \\ 1 - \phi & -\alpha & (1 - \phi) \pi_u^* \\ 0 & 0 & 0 \end{pmatrix}, \\ (b_{X_\tau}^{\pi^*}|_{u+\tau})^\top &= \begin{pmatrix} -\frac{\phi}{\tau} & 0 & -\frac{\phi}{\tau} \pi_{u+\tau}^* \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}, \quad \Phi_X(X_T) = \begin{pmatrix} 0 \\ 0 \\ e^{(1-\gamma)V_T} \end{pmatrix}, \quad L_X = 0, \\ (\sigma_X^{\pi^*})^\top &= (\sigma_{X_\tau}^{\pi^*}|_{u+\tau})^\top = \mathbf{0}_{2 \times 3 \times 3}. \end{aligned}$$

The Hamiltonian function H is given by

$$\begin{aligned} H &= \left[\frac{\phi}{\tau} (P_u - P_{u-\tau}) + (1 - \phi) \mu_u - (1 - \phi) \frac{\sigma'_S \sigma_S}{2} \right] p_u^1 + \alpha (\bar{\mu} - \mu_u) p_u^2 \\ &\quad + \left\{ -\frac{\pi_u^2 \sigma'_S \sigma_S}{2} + \pi_u \left[\frac{\phi}{\tau} (P_u - P_{u-\tau}) + \frac{\sigma'_S \sigma_S}{2} \phi + (1 - \phi) \mu_u - r \right] + r \right\} p_u^3 \\ &\quad + \sigma'_S \begin{pmatrix} z_u^{11} \\ z_u^{12} \end{pmatrix} + \sigma'_\mu \begin{pmatrix} z_u^{21} \\ z_u^{22} \end{pmatrix} + \pi_t \sigma'_S \begin{pmatrix} z_u^{31} \\ z_u^{32} \end{pmatrix}, \end{aligned}$$

so that

$$H_\pi^{\pi^*} = -\pi_u^* \sigma'_S \sigma_S + \frac{\phi}{\tau} (P_u - P_{u-\tau}) + \frac{\sigma'_S \sigma_S}{2} \phi + (1 - \phi) \mu_u - r + \sigma'_S \begin{pmatrix} z_u^{31} \\ z_u^{32} \end{pmatrix}.$$

It can be verified that $\mathbb{E}_u[H_{\pi_\tau}^{\pi^*}|_{u+\tau}] = 0$. Therefore,

$$\begin{aligned} &\langle H_\pi^{\pi^*} + \mathbb{E}_u[H_{\pi_\tau}^{\pi^*}|_{u+\tau}], \pi \rangle \\ &= \pi_u \left\{ \left[-\pi_u^* \sigma'_S \sigma_S + \frac{\phi}{\tau} (P_u - P_{u-\tau}) + \frac{\sigma'_S \sigma_S}{2} \phi + (1 - \phi) \mu_u - r \right] p_u^3 + \sigma'_S \begin{pmatrix} z_u^{31} \\ z_u^{32} \end{pmatrix} \right\}. \end{aligned}$$

Taking the derivative with respect to π_u and letting it equal zero yields

$$\begin{aligned} \pi_u^* &= \frac{\frac{\phi}{\tau} (P_u - P_{u-\tau}) + \frac{\sigma'_S \sigma_S}{2} \phi + (1 - \phi) \mu_u - r}{\sigma'_S \sigma_S} + \frac{\sigma_{S(1)} z_u^{31} + \sigma_{S(2)} z_u^{32}}{p_u^3 \sigma'_S \sigma_S} \\ &= \frac{\phi m_u + (1 - \phi) \mu_u - r}{\sigma'_S \sigma_S} + \frac{\sigma_{S(1)} z_u^{31} + \sigma_{S(2)} z_u^{32}}{p_u^3 \sigma'_S \sigma_S}, \end{aligned} \quad (\text{B.7})$$

where z_u and p_u are governed by the backward stochastic differential system (B.6). This gives the optimal investment strategy.

Especially, if $\gamma = 1$, the utility reduces to a log one and

$$\Phi_X(X_T) = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}.$$

Since the parameters and terminal values for dp_u^3 are deterministic in this case, we can assert that $z_u^{31} = z_u^{32} = 0$ for $u \in [t, T]$, which leads to $p_u^3 = 1$ for $u \in [t, T]$. Then the Hamiltonian function H is given by

$$\begin{aligned} H = & \left[\frac{\phi}{\tau}(P_u - P_{u-\tau}) + (1 - \phi)\mu_u - (1 - \phi)\frac{\sigma'_S \sigma_S}{2} \right] p_u^1 + \alpha(\bar{\mu} - \mu_u)p_u^2 \\ & + \left\{ -\frac{\pi_u^2 \sigma'_S \sigma_S}{2} + \pi_u \left[\frac{\phi}{\tau}(P_u - P_{u-\tau}) + \frac{\sigma'_S \sigma_S}{2} \phi + (1 - \phi)\mu_u - r \right] + r \right\} p_u^3 \\ & + \sigma'_S \begin{pmatrix} z_u^{11} \\ z_u^{12} \end{pmatrix} + \sigma'_\mu \begin{pmatrix} z_u^{21} \\ z_u^{22} \end{pmatrix}, \end{aligned}$$

and the optimal strategy is given by

$$\pi_u^* = \frac{\phi m_u + (1 - \phi)\mu_u - r}{\sigma'_S \sigma_S},$$

which is myopic.

APPENDIX C. ADDITIONAL OUT-OF-SAMPLE TESTS AND ROLLING WINDOW ESTIMATIONS

In this appendix, we provide some robustness analysis to out-of-sample tests and rolling window estimations.

C.1. Rolling Window Estimations. For fix $\tau = 12$, we estimate parameters of (3.2) at each month by using the past 20 years' data to avoid look-ahead bias. Fig. C.1 illustrates the estimated parameters. The big jump in estimated $\sigma_{S(1)}$ during 1930–1950 is consistent with the high volatility of market return illustrated in Fig. C.2 (b). Fig. C.1 also illustrates the interesting phenomenon: that the estimated ϕ is very close to zero for three periods of time, implying insignificant momentum but significant mean-reversion effect. By comparing Fig. C.1 (b) and (e), we observe that the insignificant ϕ is accompanied by high volatility $\sigma_{S(1)}$.

Fig. C.2 illustrates the time series of (a) the index level and (b) the simple return of the total return index of S&P 500; (c) the optimal portfolio and (d) the utility of the optimal portfolio wealth from December 1890 to December 2012 for $\tau = 12$ with 20-year rolling window estimated parameters. The index return and π_t^* are positively correlated with correlation 0.0620. In addition, we find that the profits are higher after the 1930s.

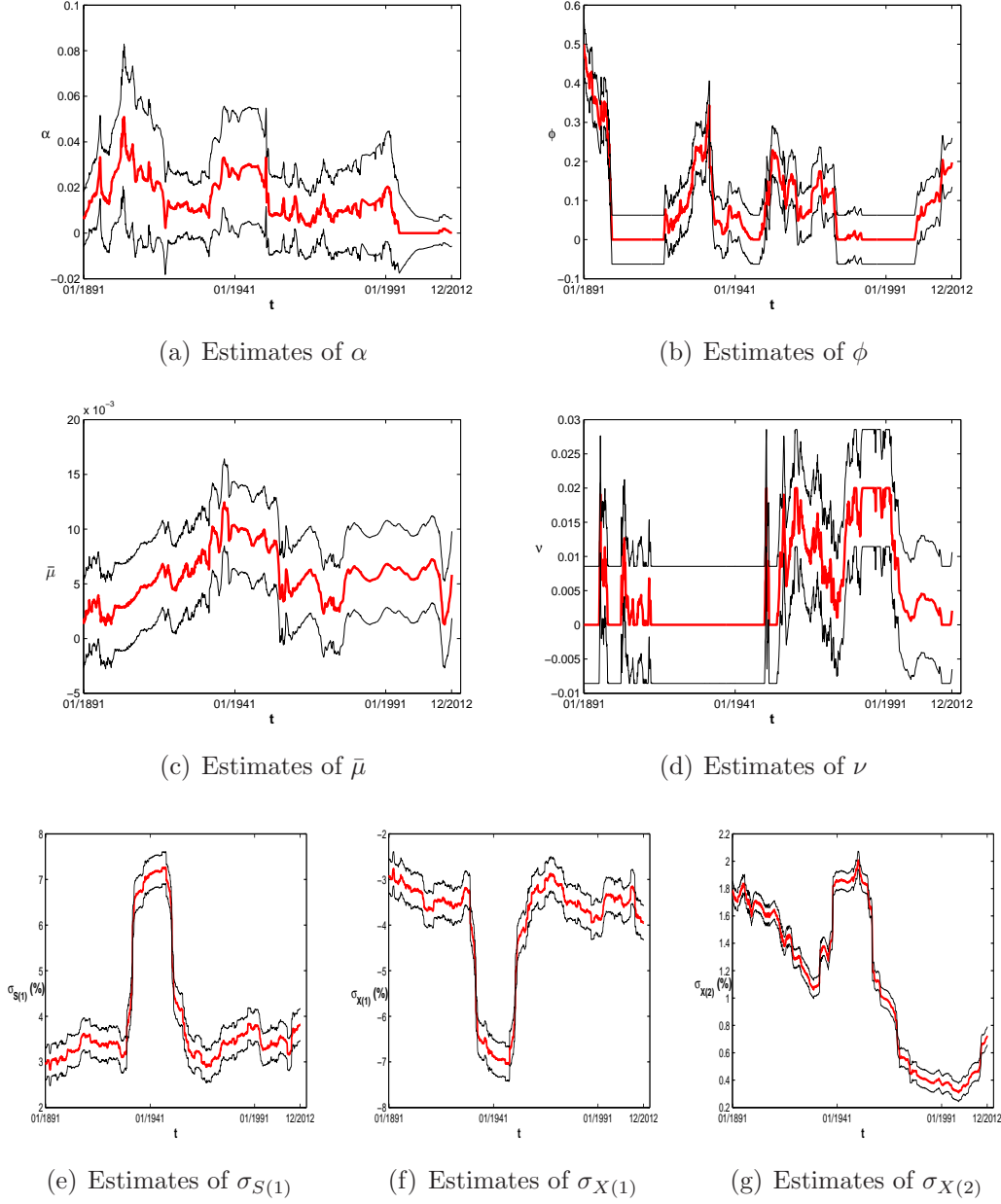


FIGURE C.1. The estimates of (a) α ; (b) ϕ ; (c) $\bar{\mu}$; (d) ν ; (e) $\sigma_{S(1)}$; (f) $\sigma_{X(1)}$ and (g) $\sigma_{X(2)}$ for $\tau = 12$ based on data from the past 20 years.

Fig. C.3 illustrates the estimates of $\sigma_{S(1)}$ for the pure momentum model ($\phi = 1$) based on data from the past 20 years; the big jump in volatility is due to the Great Depression in the 1930s. Fig. C.4 illustrates the time series of (a) the optimal portfolio and (b) the utility of wealth from December 1890 until December 2012 for $\tau = 12$ for the pure momentum model with the 20-year rolling window estimated $\sigma_{S(1)}$. By comparing Fig. C.3 and Fig. C.4 (b), the optimal strategy implied by the pure momentum model suffers huge losses during the high market volatility period.

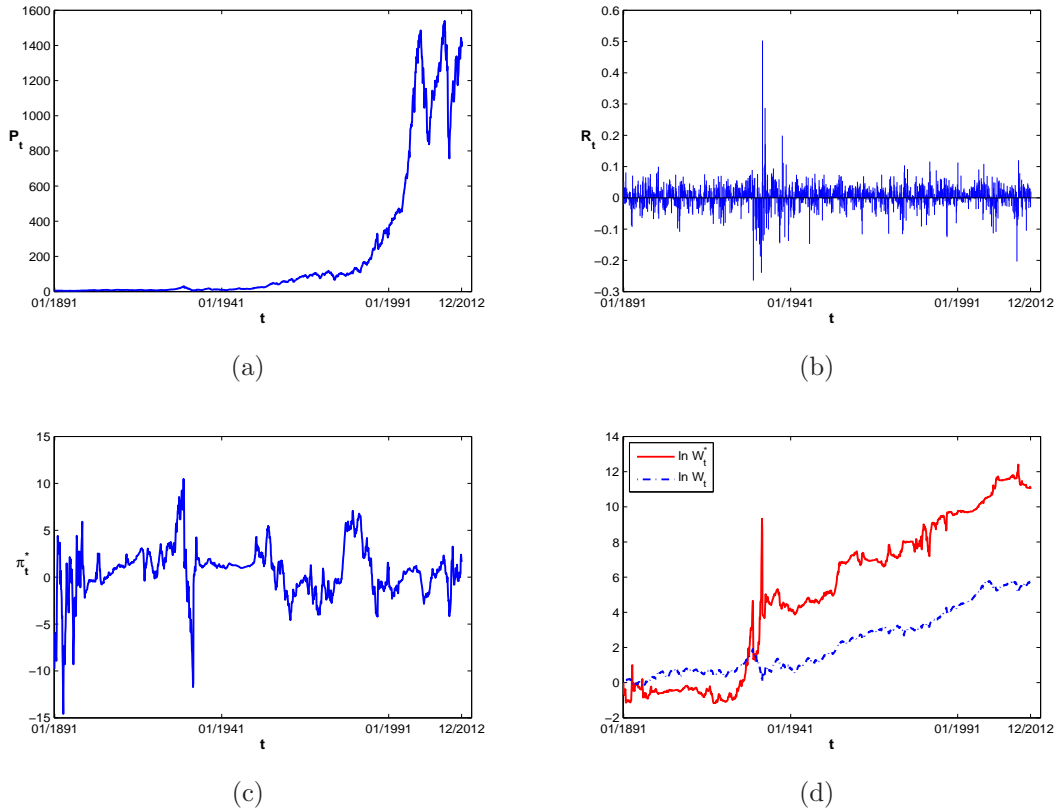


FIGURE C.2. The time series of (a) the index level and (b) the simple return of the total return index of S&P 500; (c) the optimal portfolio and (d) the utility of wealth from December 1890 until December 2012 for $\tau = 12$ with 20-year rolling window estimated parameters.

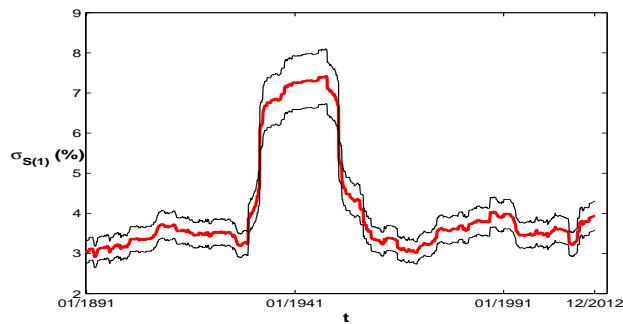


FIGURE C.3. Estimates of $\sigma_{S(1)}$ for the pure momentum model ($\phi = 1$) based on data from the past 20 years.

However, Fig C.2 illustrates that the optimal strategy implied by the full model makes big profits during the big market volatility period.

Fig. C.5 illustrates the estimated parameters for the pure mean-reversion model based on data from the past 20-years.

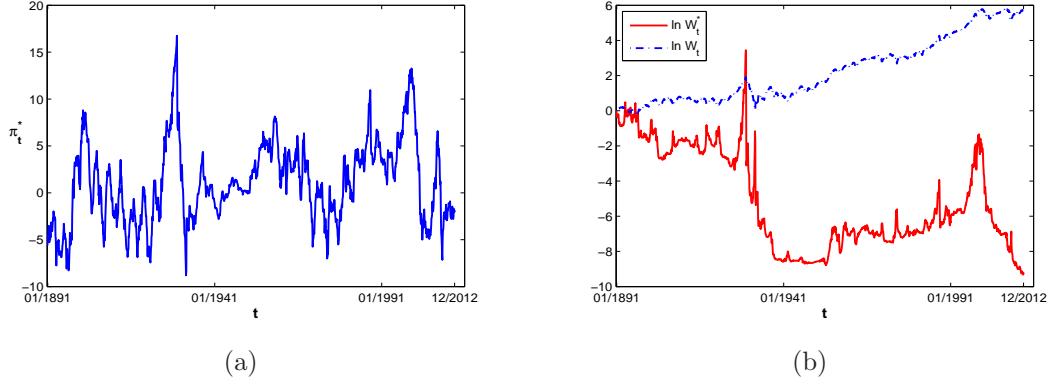


FIGURE C.4. The time series of (a) the optimal portfolio and (b) the utility of wealth from December 1890 until December 2012 for $\tau = 12$ for the pure momentum model with 20-year rolling window estimated parameters.

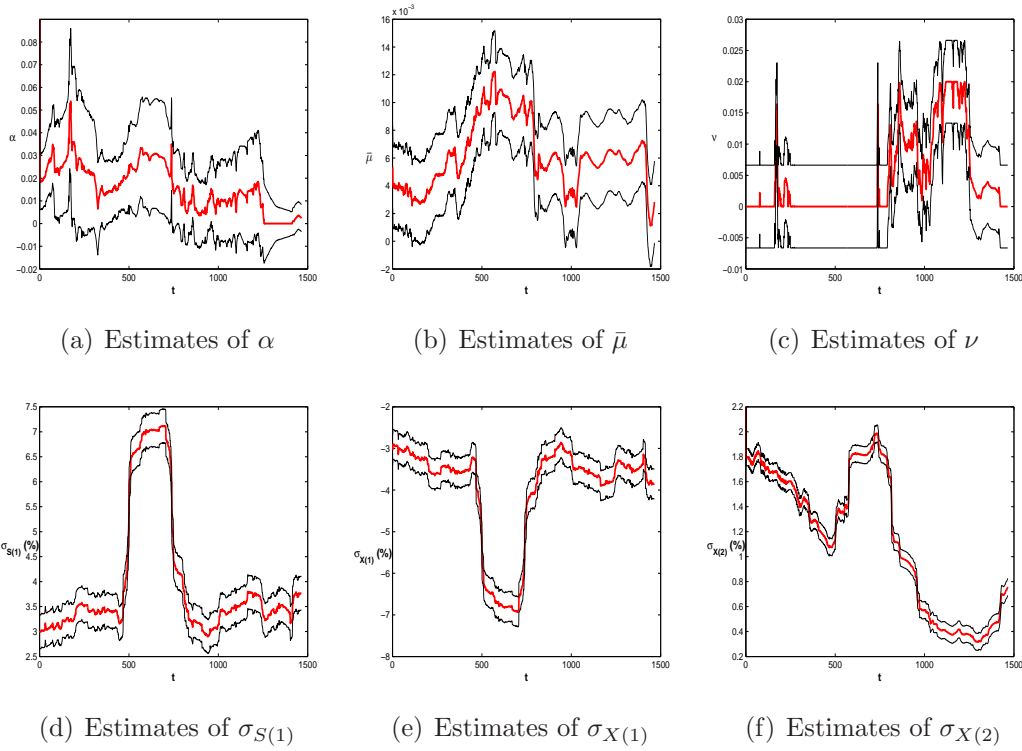


FIGURE C.5. The estimates of (a) α ; (b) ϕ ; (c) $\bar{\mu}$; (d) ν ; (e) $\sigma_{S(1)}$; (f) $\sigma_{X(1)}$ and (g) $\sigma_{X(2)}$ for the pure mean-reversion model based on data from the past 20 years.

Fig. C.6 illustrates the time series of the optimal portfolio and the utility of wealth from December 1890 until December 2012 for the pure mean-reversion model with

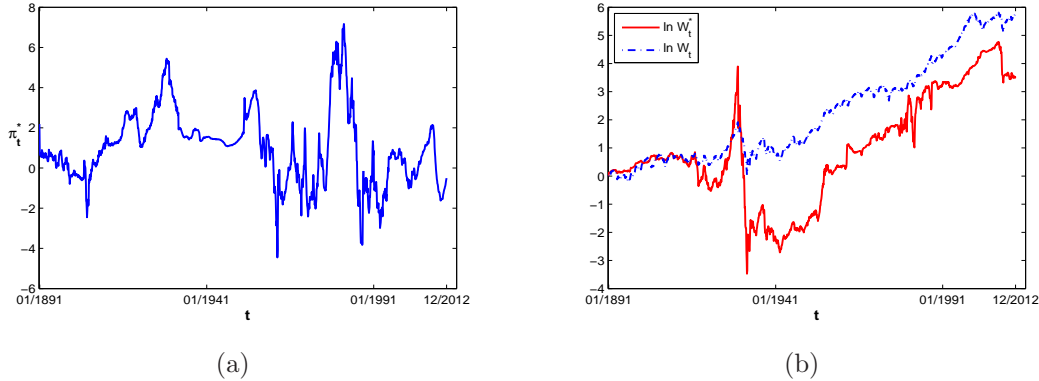


FIGURE C.6. The time series of (a) the optimal portfolio and (b) the utility of wealth from December 1890 until December 2012 for the pure mean-reversion model with 20-year rolling window estimated parameters.

20-year rolling window estimated parameters. After eliminating the look-ahead bias, the pure mean-reversion strategy cannot outperform the stock index any longer.

APPENDIX D. REGRESSIONS ON THE MARKET STATES, SENTIMENT AND VOLATILITY

D.1. Market States. First, we follow Cooper et al. (2004) and Hou et al. (2009) and define market state using the cumulative return of the stock index (including dividends) over the most recent 36 months.¹⁹ We label a month as an up (down) market month if the market's three-year return is non-negative (negative). There are 1,165 up months and 478 down months from February 1876²⁰ to December 2012.

TABLE D.1. The average excess return of the optimal strategy for $\tau = 12$.

	Observations (N)	Average excess return
Unconditional return	1,643	0.0087 (2.37)
Up market	1,165	0.0081 (4.09)
Down market	478	0.0101 (0.87)

¹⁹The results are similar if we use the alternative 6-, 12- or 24- month market state definitions, even though they are more sensitive to sudden changes in market sentiment.

²⁰We exclude January 1876 in which there is no return to the optimal strategies.

We compute the average return of the optimal strategy and compare the average returns between up and down market months. Table D.1 presents the average unconditional excess returns and the average excess returns for up and down market months. The unconditional average excess return is 87 basis points per month. In up market months, the average excess return is 81 basis points and it is statistically significant. In down market months, the average excess return is 101 basis points; this value is economically but not statistically significant. The difference between down and up months is 20 basis points, which is not significantly different from zero based on a two-sample t -test (p -value of 0.87).²¹

We use the following regression model to test for the difference in returns:

$$R_t^* - r = \alpha + \kappa I_t(UP) + \beta(R_t - r) + \epsilon_t, \quad (\text{E.1})$$

where $R_t^* = (W_t^* - W_{t-1}^*)/W_{t-1}^*$ in (3.3) is the month t return of the optimal strategy, $R_t - r$ is the excess return of the stock index, and $I_t(UP)$ is a dummy variable that takes the value of 1 if month t is in an up month, and zero otherwise. The regression intercept α measures the average return of the optimal strategy in down market months, and the coefficient κ captures the incremental average return in up market months relative to down months. We also replace the market state dummy in (E.1) with the lagged market return over the previous 36 months (not reported here), and the results are robust.

TABLE D.2. The coefficients for the regression (E.1).

	Full model	Pure momentum	Pure mean reversion	TSM
α	0.0094 (1.46)	0.0476 (1.34)	-0.0000 (-0.01)	0.0060 (3.23)
κ	0.0005 (0.06)	0.0041 (0.10)	-0.0005 (-0.32)	-0.0014 (-0.63)
β	-1.0523 (-12.48)	-6.7491 (-14.60)	0.3587 (22.97)	-0.1548 (-6.39)

Table D.2 reports the regression coefficients for the full model, the pure momentum model, pure mean-reversion model and the TSM strategy in Moskowitz et al. (2012) for $\tau = 12$ respectively. Except for the TSM, which earns significant positive returns in down market, both α and κ are insignificant for all other strategies; the results are consistent with those in Table D.1.

²¹The p -values for the pure momentum strategy, pure mean-reversion strategy and TSM are 0.87, 0.87 and 0.67 respectively.

TABLE D.3. The coefficients for the regression (E.2).

	Full model	Pure momentum	Pure mean reversion	TSM
α	0.0086 (1.44)	0.0423 (1.32)	0.0002 (0.18)	0.0058 (3.29)
κ	-0.0008 (-0.11)	-0.0034 (-0.09)	-0.0002 (-0.14)	-0.0017 (-0.81)
β_1	0.1994 (1.90)	0.7189 (1.27)	0.0708 (3.84)	0.1341 (4.30)
β_2	-2.5326 (-22.16)	-15.5802 (-25.31)	0.6991 (34.88)	-0.4964 (-14.63)

To further control for market risk in up and down market months, we now run the following regression:

$$R_t^* - r = \alpha + \kappa I_t(UP) + \beta_1(R_t - r)I_t(UP) + \beta_2(R_t - r)I_t(DOWN) + \epsilon_t. \quad (E.2)$$

The regression coefficients are reported in Table D.3. These results are similar to those in Table D.2.

TABLE D.4. The coefficients for the regression (E.3).

	Full model	Pure momentum	Pure mean reversion	TSM
α	0.0083 (1.22)	0.0409 (1.08)	0.0002 (0.14)	0.0057 (3.03)
κ	0.0006 (0.07)	0.0037 (0.08)	-0.0002 (-0.14)	-0.0012 (-0.53)

We also run the following regression:

$$R_t^* - r = \alpha + \kappa I_{t-1}(UP) + \epsilon_t, \quad (E.3)$$

and Table D.4 reports the coefficients. We find that the dummy variable of up market month has no predictive power for returns of all strategies.

TABLE D.5. The coefficients for the regression (E.4).

	Full model	Pure momentum	Pure mean reversion	TSM
α	0.0094 (1.46)	0.0476 (1.34)	0.0000 (-0.01)	0.0060 (3.23)
κ	0.0005 (0.06)	0.0041 (0.10)	-0.0005 (-0.32)	-0.0014 (-0.63)

We also study the beta-adjusted returns:

$$\begin{aligned} R_t^* - r &= \alpha^{CAPM} + \beta^{CAPM}(R_t - r) + \varepsilon_t, \\ R_t^* - r - \beta^{CAPM}(R_t - r) &= \alpha + \kappa I_t(UP) + \epsilon_t, \end{aligned} \tag{E.4}$$

and Table D.5 reports the coefficients. Again, the difference of returns between up and down months is not significant for all the strategies.

Compared with findings in Hou et al. (2009), where cross-sectional momentum returns are higher in up months, we do not find significant differences between up and down months for the strategies from our model and the TSM. Among the strategies from our model and the TSM, only the TSM has significant returns in down market months.

TABLE D.6. The coefficients for the regression (E.5).

	Full model	Pure momentum	Pure mean reversion	TSM
a	0.0059 (1.77)	0.0267 (1.74)	0.0005 (1.49)	0.0040 (2.57)
b	0.0040 (1.20)	0.0134 (0.87)	-0.0003 (-1.01)	0.0023 (1.48)

D.2. Investor Sentiment. In this subsection, we examine the relationship between the excess return of the optimal strategies and investor sentiment by running the following regression:

$$R_t^* - r = a + bT_{t-1} + \epsilon, \tag{E.5}$$

where T_t is the sentiment index measure used by Baker and Wurgler (2006). The data on the Baker-Wurgler sentiment index from 07/1965 to 12/2010 is obtained from the Jeffrey Wurglers website (<http://people.stern.nyu.edu/jwurgler/>). Table D.6 reports the coefficients. The results suggest that sentiment index has no predictive power for returns of optimal strategies and of the TSM. We also examine monthly changes of the level of sentiment by replacing T_t with its monthly changes and their orthogonalized indexes. The results are similar.

TABLE D.7. The coefficients for the regression (E.6).

	Full model	Pure momentum	Pure mean reversion	TSM
α	0.0037 (1.06)	0.0421 (1.11)	-0.0014 (-1.00)	0.0053 (2.78)
κ	0.0138 (0.25)	0.0141 (0.05)	0.0137 (1.21)	-0.0232 (-1.48)

D.3. Market Volatility. Finally, we examine the predictability of market volatility for profitability. First, we run the following regression:

$$R_t^* - r = \alpha + \kappa \hat{\sigma}_{S,t-1} + \epsilon_t, \quad (\text{E.6})$$

where the ex-ante annualized volatility $\hat{\sigma}_{S,t}$ is given by (3.6). Table D.7 reports the results. We see that volatility has no predictive power for returns of optimal strategies and of the TSM.

TABLE D.8. The coefficients for the regression (E.7).

	Full model	Pure momentum	Pure mean reversion	TSM
α	-0.0020 (-0.27)	-0.0151 (-0.36)	0.0012 (0.80)	0.0025 (1.19)
κ_1	0.1043 (1.34)	0.5763 (1.33)	-0.0127 (-0.80)	0.0016 (-0.07)
κ_2	0.1026 (1.80)	0.5564 (1.75)	-0.0098 (-0.84)	0.0084 (0.53)

Second, we run the regression by following Wang and Xu (2012):

$$R_t^* - r = \alpha + \kappa_1 \hat{\sigma}_{S,t-1}^+ + \kappa_2 \hat{\sigma}_{S,t-1}^- + \epsilon_t, \quad (\text{E.7})$$

where $\hat{\sigma}_{S,t}^+$ ($\hat{\sigma}_{S,t}^-$) is equal to $\hat{\sigma}_{S,t}$ if the market state is up (down) and otherwise equal to zero. Table D.8 reports the coefficients. The results are similar to those in Table D.7 even if we distinguish volatility in up and down market months.

APPENDIX E. COMPARISON WITH MOSKOWITZ, OOI AND PEDERSEN (2012)

TABLE E.1. The average excess return (%) of the optimal strategies for different look-back period τ (different row) and different holding period h (different column).

$(\tau \setminus h)$	1	3	6	9	12	24	36	48	60
1	0.1337 (1.28)	0.1387 (1.84)	0.1874* (3.29)	0.1573* (2.83)	0.0998 (1.84)	0.0222 (0.42)	0.0328 (0.63)	0.0479 (0.90)	0.0362 (0.66)
3	0.0972 (0.93)	0.0972 (0.93)	0.0972 (0.93)	0.0972 (0.93)	0.0972 (0.93)	0.0972 (0.93)	0.0972 (0.93)	0.0972 (0.93)	0.0972 (0.93)
6	0.2022 (1.93)	0.2173* (2.28)	0.2315* (2.60)	0.1462 (1.75)	0.0700 (0.88)	-0.0414 (-0.58)	0.0199 (0.32)	0.0304 (0.53)	0.0014 (0.02)
9	0.3413* (3.27)	0.3067* (3.12)	0.2106* (2.28)	0.1242 (1.45)	0.0333 (0.41)	-0.0777 (-1.16)	-0.0095 (-0.17)	0.0000 (0.00)	-0.0450 (-1.11)
12	0.1941 (1.85)	0.1369 (1.40)	0.0756 (0.80)	-0.0041 (-0.04)	-0.0647 (-0.76)	-0.0931 (-1.30)	-0.0234 (-0.41)	-0.0137 (-0.30)	-0.0587 (-1.46)
24	-0.0029 (-0.03)	-0.0513 (-0.51)	-0.0776 (-0.79)	-0.0591 (-0.62)	-0.0557 (-0.61)	-0.0271 (-0.34)	0.0261 (0.40)	-0.0020 (-0.03)	-0.0082 (-0.15)
36	0.0369 (0.35)	0.0602 (0.59)	0.0517 (0.52)	0.0419 (0.43)	0.0416 (0.44)	0.0657 (0.81)	0.0351 (0.49)	0.0273 (0.42)	0.0406 (0.64)
48	0.1819 (1.74)	0.1307 (1.30)	0.1035 (1.06)	0.0895 (0.93)	0.0407 (0.43)	-0.0172 (-0.21)	0.0179 (0.24)	0.0500 (0.70)	0.0595 (0.86)
60	-0.0049 (-0.05)	-0.0263 (-0.26)	-0.0800 (-0.81)	-0.1160 (-1.20)	-0.1289 (-1.41)	-0.0396 (-0.49)	0.0424 (0.55)	0.0518 (0.69)	0.0680 (0.92)

APPENDIX F. THE EFFECTS OF TIME HORIZONS

F.1. Information Criteria. We present different information criteria, including Akaike (AIC), Bayesian (BIC) and Hannan–Quinn (HQ) information criteria for τ from one month to 60 months in Fig. F.1. We see that the AIC, BIC and HQ reach their minima at $\tau = 23, 19$ and 20 respectively. Also, we observe a common increasing pattern of the criteria level for longer τ .

TABLE E.2. The average excess return (%) of the optimal strategies for different look-back period τ (different row) and different holding period h (different column) for the pure momentum model.

$(\tau \setminus h)$	1	3	6	9	12	24	36	48	60
1	-0.0144 (-0.14)	0.0652 (0.89)	0.0714 (1.34)	0.0689 (1.52)	0.0568 (1.37)	-0.0040 (-0.12)	0.0006 (0.02)	0.0010 (0.04)	-0.0133 (-0.57)
3	0.1683 (1.61)	0.1915* (2.16)	0.1460 (1.91)	0.1536* (2.20)	0.0764 (1.17)	-0.0360 (-0.69)	-0.0290 (-0.72)	-0.0143 (-0.45)	-0.0395 (-1.38)
6	0.2906* (2.78)	0.2633* (2.79)	0.2635* (3.01)	0.1884* (2.29)	0.1031 (1.34)	-0.0484 (-0.75)	-0.0130 (-0.26)	0.0157 (0.40)	-0.0281 (-0.77)
9	0.4075* (3.91)	0.3779* (3.78)	0.2422* (2.62)	0.1538 (1.76)	0.0545 (0.66)	-0.0735 (-1.05)	-0.0217 (-0.38)	-0.0047 (-0.10)	-0.0460 (-1.12)
12	0.2453* (2.35)	0.1660 (1.67)	0.0904 (0.94)	0.0122 (0.13)	-0.0748 (-0.86)	-0.1195 (-1.63)	-0.0602 (-1.02)	-0.0454 (-0.95)	-0.0798 (-1.88)
24	0.0092 (0.09)	-0.0242 (-0.24)	-0.0800 (-0.81)	-0.0962 (-1.03)	-0.0955 (-1.06)	-0.0682 (-0.88)	-0.0081 (-0.13)	-0.0140 (-0.24)	-0.0211 (-0.39)
36	-0.0005 (-0.01)	0.0194 (0.19)	0.0219 (0.23)	0.0212 (0.22)	0.0113 (0.12)	0.0030 (0.04)	0.0127 (0.18)	0.0241 (0.37)	0.0206 (0.33)
48	0.0779 (0.74)	0.0733 (0.73)	0.0231 (0.24)	0.0019 (0.02)	-0.0392 (-0.42)	-0.0676 (-0.83)	-0.0004 (-0.01)	0.0435 (0.61)	0.0382 (0.55)
60	-0.0568 (-0.54)	-0.0852 (-0.84)	-0.1403 (-1.41)	-0.1706 (-1.77)	-0.1986 (-2.15)	-0.1091 (-1.36)	-0.0043 (-0.06)	0.0157 (0.22)	0.0239 (0.34)

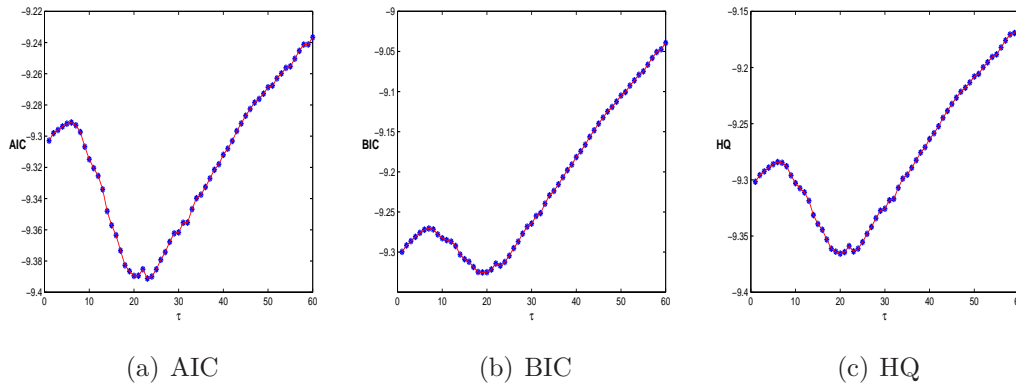


FIGURE F.1. (a) Akaike information criteria, (b) Bayesian information criteria, and (c) Hannan–Quinn information criteria for $\tau \in [1, 60]$.

F.2. The Estimation and Log-likelihood Ratio Test for the Pure Momentum Strategy. We present the estimation of parameter $\sigma_{S(1)}$ for the pure momentum model in Fig. F.2(a) for $\tau \in [1, 60]$. We also present the results of the

log-likelihood ratio test to compare the full model to the estimated pure momentum model ($\phi = 1$) and pure mean-reversion model with respect to different τ in Fig. F.2 (b), where the solid red line shows the test statistic when compared to the pure momentum model. The statistic is much greater than 12.59, the critical value with six degrees of freedom at the 5% significance level. The dash-dotted blue line illustrates the test statistic when comparing to the pure mean-reversion model. The test statistic is much greater than 3.841, the critical value with one degree of freedom at 5% significance level.

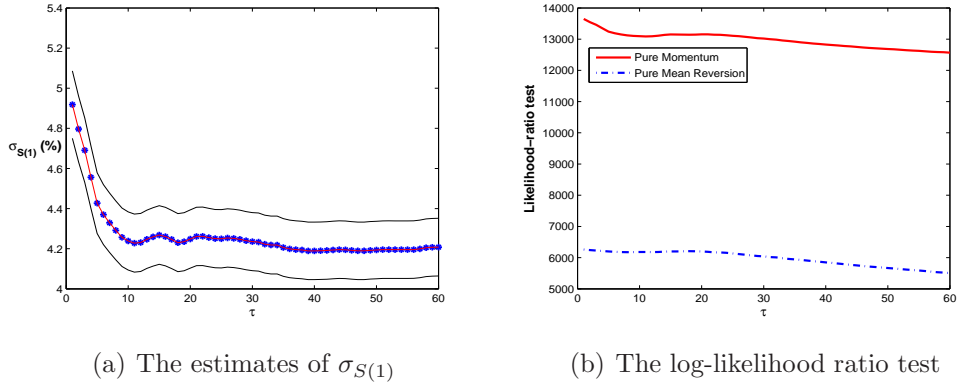


FIGURE F.2. The estimates of $\sigma_{S(1)}$ for the pure momentum model (a) and the log-likelihood ratio test (b) for $\tau \in [1, 60]$.

F.3. The Performance for Different Time Horizons. To compare with the performance of the pure momentum strategies to the market index, based on estimated parameters in Fig. F.2, we report the terminal utilities of the portfolios of the pure momentum model at December 2012 in Fig. F.3.

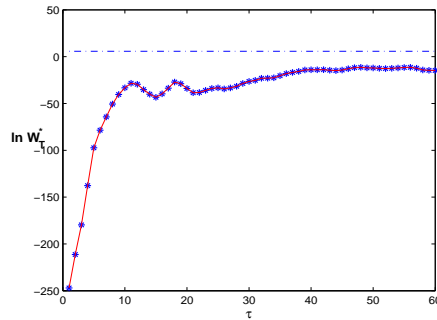


FIGURE F.3. The utility of terminal wealth of the pure momentum model for $\tau \in [1, 60]$.

For $\tau = 1, 2, \dots, 60$, Fig. F.4 illustrates the evolution of the utility of the optimal portfolio wealth (the dark and more volatile surface) and of the passive holding

index portfolio (the yellow and smooth surface) from January 1876 until December 2012. It indicates that the optimal strategies outperform the market index for τ from five months to 20 months consistently.

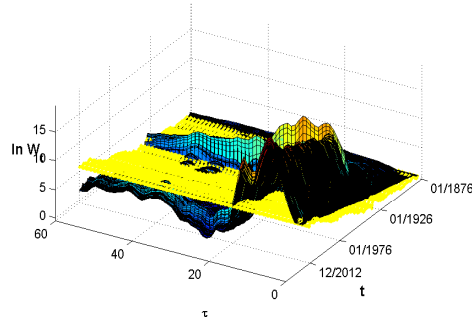


FIGURE F.4. The utility of the optimal portfolio wealth from January 1876 until December 2012 comparing with the passive holding portfolio for $\tau \in [1, 60]$.

F.4. The Out-of-sample Test for Different Time Horizons. To see the effect of the time horizon on the results of out-of-sample tests, we split the whole data set into two equal periods: January 1871–December 1941 and January 1942–December 2012. For given τ , we estimate the model for the first sub-sample period and do the out-of-sample test over the second sub-sample period. We report the utility of terminal wealth for $\tau \in [1, 60]$ using sample data of the last 71 years in Fig. F.5. Clearly the optimal strategies still outperform the market for $\tau \in [1, 14]$.

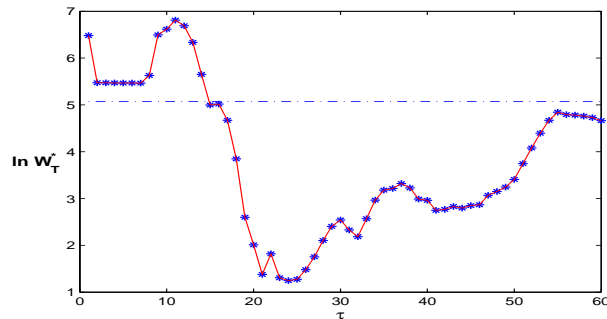


FIGURE F.5. The utility of terminal wealth for $\tau \in [1, 60]$ based on the out-of-sample period January 1942 to December 2012.

F.5. Rolling Window Estimates for Different Time Horizons. We also implement rolling window estimations for different time horizons. Fig. F.6 illustrates the correlations of the estimated $\sigma_{S(1)}$ with (a) the estimated ϕ and the return of the optimal strategies for (b) the full model, (c) the pure momentum model and (d)

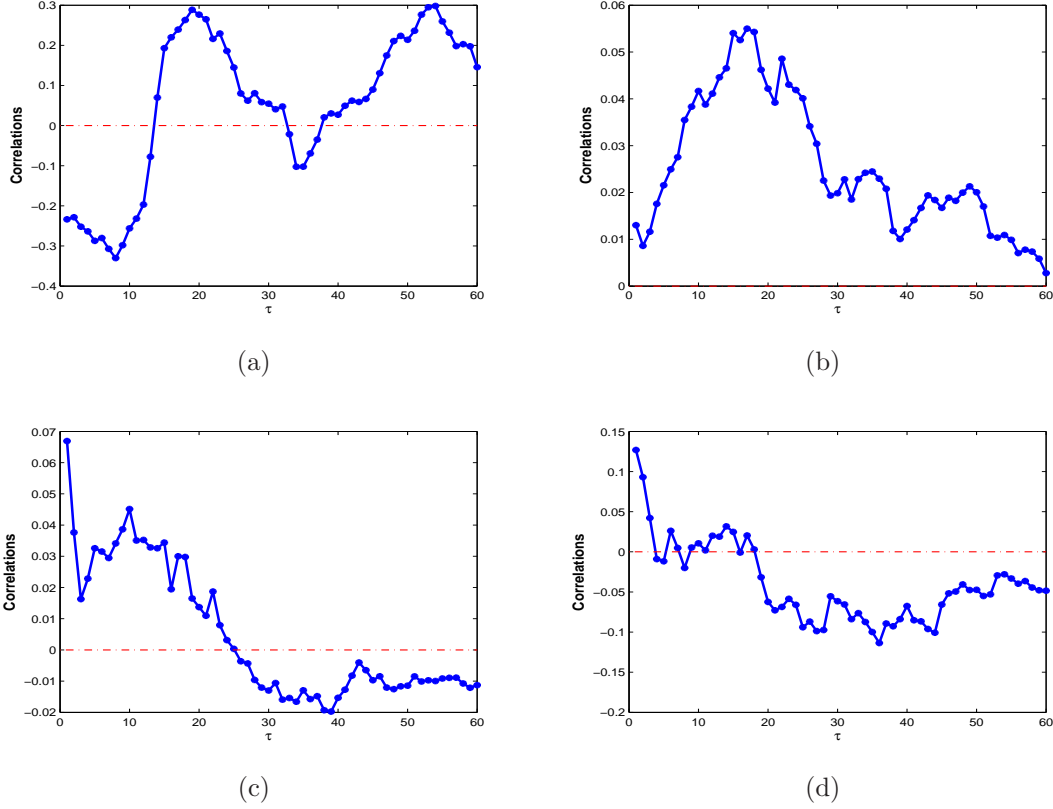


FIGURE F.6. The correlations of the estimated $\sigma_{S(1)}$ with (a) the estimated ϕ and the return of the optimal strategies for (b) the full model, (c) the pure momentum model and (d) the TSM return.

the TSM return for $\tau \in [1, 60]$. Interestingly, higher volatility is accompanied by a less significant momentum effect with small time horizons ($\tau \leq 13$). But ϕ and $\sigma_{S(1)}$ are positive correlated when the time horizon becomes large. One possible reason is that a long time horizon makes the trading signal less sensitive to changes in price and hence the trading signal is significant only when the market price changes dramatically in a high volatility period. Fig. F.6 (c) and (d) show that the profitability of the optimal strategies for the pure momentum model and the TSM strategies are sensitive to the estimated market volatility. The return is positively (negatively) related to market volatility for short (long) time horizons. But Fig. F.6 (b) shows that the optimal strategies for the full model perform well even in a highly volatile market.

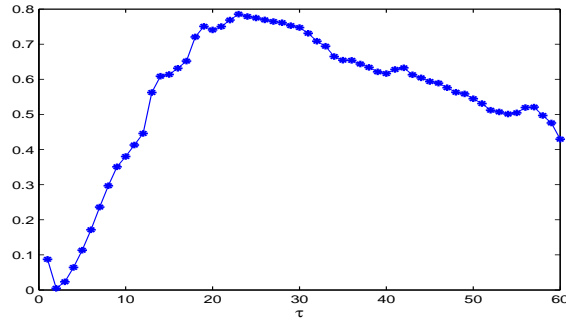


FIGURE F.7. The fraction of ϕ significantly different from zero for $\tau \in [1, 60]$.

We also study other time horizons. We find that the estimates of $\sigma_{S(1)}$, $\sigma_{X(1)}$ and $\sigma_{X(2)}$ are insensitive to τ but the estimates of ϕ are sensitive to τ . Fig. F.7 illustrates the corresponding fraction of ϕ , which is significantly different from zero for $\tau \in [1, 60]$. It shows that the momentums with 20–30 month horizons occur most frequently during the period from December 1890 until December 2012.

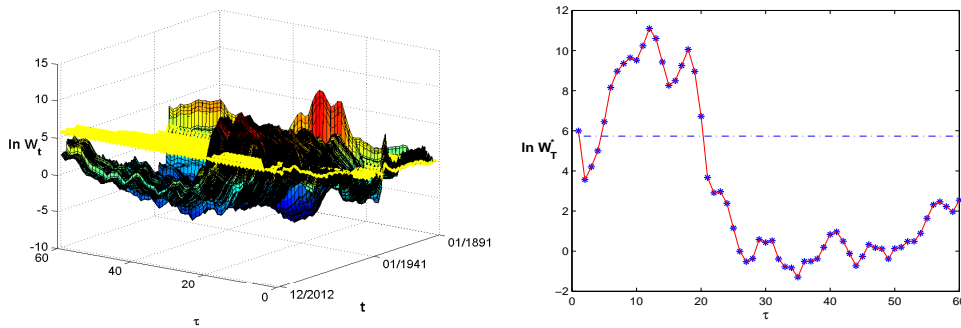


FIGURE F.8. The utility of wealth from December 1890 to December 2012 for the optimal portfolio with $\tau \in [1, 60]$ and the passive holding portfolio with 20-year rolling window estimated parameters.

Fig. F.8 (a) illustrates the utility of wealth from December 1890 until December 2012 for the optimal portfolio with $\tau \in [1, 60]$ and the passive holding portfolio. Especially, the utility of terminal wealth illustrated in Fig. F.8 (b) shows that the optimal strategies work well for short horizons $\tau \leq 20$ and the terminal utility reaches its peak at $\tau = 12$.

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