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INFLATION AND THE SUBSEQUENT TIMING OF THE CHINESE STOCK MARKET

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ABSTRACT

This paper examines market-timing strategies based on inflation in a sample of three stock market indices drawn from the Shanghai and the Shenzhen Stock Exchanges between February 2002 and May 2010. Specifically, this study investigates the effectiveness of market-timing activity and its stability over time when using inflation. Consistent with previous studies, the results reveal significantly strong information conveyed through inflation in helping investors earn profits in excess of a buy-and-hold strategy. The nature of the information and the subsequent importance of the corresponding market-timing activity change over time, providing new evidence of time-varying investment opportunities in the Chinese stock market. The results of this study imply that the Chinese stock market has predictable components that can be exploited using information on inflation. However, this practice might experience time variations in a real-time framework, which draws investors' attention to asset allocation under economic uncertainty.

Keywords: inflation, market return, market timing, time variation

INTRODUCTION

Market timing has attracted the attention of both academics and practitioners for several decades, particularly because the potential gains from perfect market timing are enormous compared to the widely recommended buy-and-hold strategy (Bauer & Dahlquist, 2001). Theoretically, any attempt to obtain performance superior to that of the overall 'market portfolio' by picking and choosing among securities would fail in an efficient market (Sharpe, 1975), indicating that investors are better off not trying because accurate market timing is difficult when inefficiencies are few. However, asking investors not to 'time the market' is equivalent to asking consumers not to maximise their utilities when making consumption decisions (Shen, 2003).

An important issue commonly associated with market timing is the development of market-timing strategies that can add value to the investment management process, including the selection of predictor variables and the construction of forecasting methods. As described by Abraham and Ledolter (2005), the ability to form good forecasts depends on both predictor variables and forecasting methods.

Since the early work of Chen, Roll and Ross (1986), many studies have attempted to empirically explore the role of macroeconomic variables in explaining security returns given their theoretical importance: based on multifactor asset-pricing models, any variable that affects the set of future investment opportunities or the level of consumption (given wealth) should be priced in equilibrium (Merton, 1973). Macroeconomic variables are excellent candidates for these extra-market risk factors because (1) macro changes may influence companies' cash flows as well as the risk-adjusted discount rate and (2) macro changes may also influence the number and the types of real investment opportunities available (Flannery & Protopapadakis, 2002).

Examples of these studies include a study by Rapach (2001), who tests the effects of the money supply, aggregate spending and aggregate supply shocks on real US stock returns, with the results indicating that each macro shock has important effects on returns. Fang, Lin and Parbhoo (2008) examine the effects of news surprises of macroeconomic announcements on Australian financial markets, highlighting the importance of news about the consumer price index (*CPI*). In terms of emerging markets, Wongbangpo and Sharma (2002) examine the role of macroeconomic variables, namely the gross national product (*GNP*), *CPI*, money supply, the interest rate, and the exchange rate on stock returns in five ASEAN countries (Indonesia, Malaysia, Philippines, Singapore and Thailand), and find long- and short-term relationships between these variables and stock returns. Abugri (2008) tests whether the dynamics in key macroeconomic variables such as exchange rates, interest rates, industrial production and the money supply in four Latin American countries (Argentina, Brazil, Chile and Mexico) significantly explain stock returns. The results show that shocks from the variables are transmitted to markets at varying magnitudes and significance.

In summary, to date, the literature has partly detailed some difficulty in ascertaining the impact of real-sector macroeconomic variables on stock returns. However, more reliable relationships have been documented between a few macroeconomic variables including inflation and stock returns.

Many academics have also formulated various forecasting methods based on macroeconomic variables to time the market. For example, Marquering and

Verbeek (2004) construct a number of alternative trading strategies based on linear regression models and provide solid support for market timing. By contrast, Qi (1999) examines market-timing strategies based on a non-linear system that requires dynamic learning from observed data, finding that the switching portfolio based on the recursive neural-network forecasts produces higher profits with lower risks than both the buy-and-hold market portfolio and the switching portfolio based on linear recursive forecasts. Resnick and Shoesmith (2002) extend a probit model used to forecast economic recessions to forecast bear stock market periods and test market-timing strategies based on the model. The results support the model as reliable in forecasting stock market turning points one month in advance, which is economically significant.

In this paper, we focus on inflation from amongst a range of macroeconomic variables. In theory, inflation affects stock returns because it raises the expectation of a more restrictive (unrestrictive) monetary policy, which impacts the nominal rate of interest, and may discourage (encourage) investment, which reduces (raises) the expectation of future cash flows (Chen et al., 1986). Empirical studies have found a strong relationship between inflation and stock returns, suggesting the potential ability of inflation to predict future stock price changes (e.g., Marquering & Verbeek, 2004; Geetha, Mohidin, Chandran, & Chong, 2011; Kuwornu et al., 2011). Particularly, Ray (2012) finds that a significant relationship exists between inflation and stock returns in Asian economies, including those of India, Hong Kong, Singapore, Japan and Korea over the period from 2002 to 2010. It is arguable that the same relationship may exist in the Chinese case as a result of the government's long-term policy with investment as the main source of China's economic growth since the 1978 reform and an "opening up" of the market, which may consequently increase inflation as well as asset prices given the limited investment venues available in China (Wei, Chen, & Zhai, 2010). This is strongly supported by Geetha et al. (2011), who find that there are both short-run and long-run relationships between inflation and Chinese stock returns. The evidence therefore motivates us to study the forecasting ability of inflation on future stock price movements (or specifically stock market downturns) in China and corresponding market-timing strategies.

The study of the predictability of China's stock market performance will contribute to the extant literature, which intensively focuses on developed markets. To the best of our knowledge, little effort has been devoted to investigating the predictability issue in the Chinese stock market. The Chinese stock market has grown at a phenomenal pace since its inception in the early 1990s and has received substantial media coverage in recent years. However, the general perception of these markets is less than adulatory, with depictions of them as opaque, chaotic, inefficient, and rather irrational (Eun & Huang, 2007). The associated abnormal performance and excessive volatility therefore provide a great opportunity to test the robustness of market timing. Previous studies on the Chinese stock market have so far focused on pricing behaviour and the efficiency of the market, market segmentation and explanations for price differentials among classes of stocks, market impediments and governmental factors, as well as corporate governance issues and initial public offerings (IPOs) (Chan, Fung, & Thapa, 2007). More recent studies attempt to link the Chinese stock market to international shocks (Cheng & Glascock, 2006; Li, 2007; Kozluk, 2008).

One important issue with most of the literature on market timing is the assumption of model constancy, which is quite common because finance has long been influenced by the mantra of ‘time invariance'. Such an assumption has encountered challenges more recently. Bossaerts and Hillion (1999) find that stock returns on a range of US and international portfolios are largely unpredictable during out-of-sample periods. Paye and Timmermann (2006) estimate the models of stock returns for a set of international stock markets, finding support for the model instability for the vast majority of countries. Theoretically, model instability arises from a number of factors, including major changes in market sentiment, bursts or the creation of speculative bubbles, and regime switches in monetary and debt-management policies (for example, from targeting the money supply to targeting inflation or from short-term to long-term debt instruments) (Pesaran & Timmermann, 2002). These possibilities are important because they might introduce new risks that are ignored by traditional studies and therefore are highly likely to fundamentally affect the extent to which stock returns are predictable.

The evidence therefore motivates the development of statistical tests for potential time variations in the relationships between macroeconomic variables and stock returns, such as the Bai-Perron method (Bai & Perron, 1998) and the reversed ordered cumulative sum (CUSUM) method (Pesaran & Timmermann, 2002). This research extends these statistical methods to market-timing activity.

The paper addresses two main issues concerning market timing. Firstly, this study formulates market-timing strategies based on inflation, which is accomplished by examining the signalling power of inflation when inflation extends beyond the historical ranges. Secondly, this study examines whether the importance of the market-timing strategies based on inflation experience time variations during the study period and how these variations affect the results. Therefore, the paper adds to the literature in terms of whether stock prices fully incorporate all publicly available information in China by formulating easy-to-implement rather than technically complicated market-timing strategies. It also improves on most previous studies by testing time-varying investment opportunities in the Chinese stock market.

METHODOLOGY

Sample and Data Description

The data set involves monthly data that cover the period from February 2002 to May 2010, given the availability of the bond data. We use the Shanghai A-Share Index (*SHA*), the Shanghai Composite Index (*SHC*) and the ChinaBond Composite Bond Index (maturity of less than 1 year) (*CCB*) from the Shanghai Stock Exchange (*SHSE*), and the Shenzhen Composite Index (*SZC*) from the Shenzhen Stock Exchange (*SZSE*) in China. Particularly, the *SHA* together with the *CCB* are used as a baseline study, with the rest of the indices tested as a robustness check. The predictor variables are the yearly inflation rates based on both *CPI* and production price index (*PPI*) (I_{cpi} and I_{ppi}) and the changes of the yearly inflation rates (ΔI_{cpi} and ΔI_{ppi}). All of the data are compiled from Thomson Reuters DataStream and www.chinabond.com.cn.

Variable Definitions and Modelling and Estimation Methods

The market indices in our study are value-weighted indices, the examination of which is motivated by their use in previous empirical studies (Fama & Schwert, 1977; Breen, Glosten, & Jagannathan, 1989). Particularly, the *SHA* comprises all of the listed A-shares traded on the *SHSE*. Likewise, the same is true for the *SHC* and the *SZC*. By contrast, the *CCB* is an index of all bonds with a maturity of less than 1 year traded on the *SHSE*. For the trading day at the end of each month in the investigated period, we have both stock price data (without dividends) and bond price data (without coupons) and subsequently calculate the monthly index returns as:

$$R_{s,t} = \log \frac{p_{s,t}}{p_{s,t-1}} \quad \text{and} \quad R_{b,t} = \log \frac{p_{b,t}}{p_{b,t-1}}$$

where R_s = the stock index return; R_b = the bond index return; P_s = the net price (without dividends) of the stock index; P_b = the net price (without coupons) of the bond index. The subscripts t and $t-1$ indicate months t and $t-1$, respectively.

Inflation is a rise in the general level of the prices of goods and services in an economy over a certain period of time and thus is considered as a general economic state variable that will influence the pricing of large stock market aggregates (Chen et al., 1986). The relevant non-seasonally adjusted data, measured by both *CPI* and *PPI*, are presented by the National Bureau of Statistics in China around the 15th of each month, providing information concerning inflation during the preceding month. We calculate the inflation variables as follows:

$$I_t = \log \frac{pI_t}{100} \quad \text{and} \quad \Delta I_t = I_t - I_{t-12}$$

where I = the yearly inflation rates using both *CPI* and *PPI* with the same period of the previous year set to 100; ΔI = the changes in I over the last 12 months using both *CPI* and *PPI*; *PI* = the corresponding price index. The subscripts t and $t - 12$ indicate months t and $t - 12$, respectively.

To examine the forecasting ability of inflation on subsequent stock market downturns, this study employs the methodology proposed by Shen (2003). Consider an investor who believes that stock returns follow a mean-reversion process and can be predicted by a set of macroeconomic variables but does not know the 'true' form of underlying specification let alone the 'true' value of the parameters. Under these circumstances, the best strategy followed by the investor could be to passively remain in the stock market except on the occasions when the market is overpriced.

Suppose that at each point in time t , an investor makes forecasts of market downturns one period ahead using the information publicly available at the time. The forecasting model (denoted by *M*) is given by

$$M: R^e_{s,t} = R_{s,t} - R_{b,t} \sim (x_{t-1}) \qquad t = 1, 2, 3, \ldots, n$$

where R_s^e = the excess market return with the direction rather than the magnitude of relevance; x_t = the inflation variable chosen by the investor. $R_{s,t}$ and $R_{b,t}$ are described as before. The subscripts t and $t - 1$ indicate months t and $t - 1$, respectively.

We describe the investor's decision procedures as identifying the occasions when the stock market is overpriced using inflation so that investors are better off avoiding it, with the assumption based on the belief that average asset prices generally incorporate fundamentals. However, at rare times, even aggregate market prices diverge widely from fundamentals, which may be hinted at by inflation variables. For example, moderate inflation can enable a boost to economic growth, which also benefits asset prices. However, when inflation is extremely high, investors would expect restrictive monetary policy on the nominal rate of interest, consequently depressing asset prices.

Particularly, we focus on the periods when inflation exceeds its historical 90th percentile thresholds. Every month, the threshold is updated by deleting the oldest observation and adding a new observation. If inflation crosses the 90th percentile thresholds, it implies that the stock market price is highly expensive and that an imminent fall is likely. Consequently, the entire portfolio is liquidated at the end-of-month market price and invested in the bond market for the next entire month. Otherwise, the portfolio is invested in the stock market for the next entire month.

When evaluating the signalling power, we examine whether the information from inflation can generate predictions with value for investors by using a non-parametric test (Henriksson & Merton, 1981). We also estimate whether the excess stock market performs very differently when inflation extends beyond its 90th percentile thresholds as a robustness check.

We further formulate market-timing strategies using inflation and compare them to buying and holding the stock market index all the time. Particularly, we assume that our investor is risk-neutral, maximising the risk-return trade-off by switching his/her wealth between the stock market and the bond market. For a certain level of wealth, the investor's optimisation problem is given by

$$\max_{K_t}\left(E_t\left\{R_{p,t}\right\}, Risk\left\{R_{p,t}\right\}\right)_{t=2\ldots n}$$

where K_t = the proportion of the portfolio allocated to the security market, which is 100% in our case; $E_t\{R_{p,\,t}\}$ = the expected return of the portfolio; $Risk_t\{R_{p,\,t}\}$ = the expected risk of the portfolio; $R_{p,t}$ = the return of the portfolio, which depends on the forecast at time $t-1$. The subscript t indicates month t.

The critical elements in the equation represent the conditional expectation and the conditional risk of the portfolio. In the following tests, we approximate these moments with our forecasting model using the traditional metrics such as the Sharpe Ratio and Jensen's Alpha.

$$\text{Sharpe Ratio}_t = \frac{\frac{1}{t}*\Sigma_{i=1}^{t}\left(R_{p,i}-R_{f,i}\right)}{\sqrt{\frac{1}{t}*\Sigma_{i=1}^{t}\left(R_{p,i}-\overline{R}_{p,i}\right)^2}}$$

$$\text{Jensen's Alpha}_t = \overline{R}_{p,t}-\left[R_{f,t}+\beta_{tM}*\left(R_{s,t}-R_{f,t}\right)\right]$$

where $\overline{R}_{p,t}$ = the average return of the portfolio; $R_{f,t}$ = the risk-free rate; β_{tM} = the beta of the portfolio. $R_{p,t}$ and $R_{s,t}$ are described as above. The subscripts *i* and *t* indicate months *i* and *t*, respectively.

The exception is when the portfolio return distributions are significantly non-normal, under which using the traditional metrics would ignore the distribution property and thus be misleading. To address this shortcoming, we employ the Omega Ratio ($\Omega(r)$), defined as the probability-weighted ratio of gains to losses relative to the threshold *r* (Keating & Shadwick, 2002).

$$\text{Omega Ratio } \Omega(r) = \int_r^b (1 - F(x))dx \,/ \int_a^r (F(x))dx$$

where *r* = the target return that the investor is interested in; (a,b) = the interval of returns; $F(.)$ = the cumulative distribution of returns.

Our approach requires no assumption about portfolio return distributions. For example, we do not assume that return distributions are necessarily normal and therefore choose to report both the traditional metrics and the Omega Ratio, which enables us to compare the statistics and evaluate the difference in their implications.

EMPIRICAL RESULTS AND DISCUSSIONS

Summary Statistics

The basic summary statistics for the monthly financial market series and the inflation variables are shown in Panel A of Table 1. As expected, the stock index had a higher average return than the bond index, accompanied by higher volatility. Both the returns for the excess market and the stock index exhibited slightly negative skewness, suggesting that negative returns were larger than positive returns. All three series were further characterised by a certain degree of kurtosis in their return distributions. Over the same period, the inflation rate had been low and remained mostly within the 3% target band established by the government.

Panel B further divides the series into positive and negative values, subsequently examining their distribution characteristics. On average, it shows that the stock market performed better than the bond market, with 59 positive excess market returns relative to 41 negative returns. The dominant number of positive inflation rates also suggests the existence of some price pressure in China during the study period.

Table 1
Summary statistics

Panel A: Basic statistics							
	Mean	Median	St. Dev.	Skewness	Kurtosis	Max	Min
Stock and bond returns							
R_s	0.0024	0.0083	0.0402	–0.6269	4.0247	0.1059	–0.1226
R_b	–0.0001	–0.0001	0.0005	0.6202	5.5323	0.0017	–0.0018
R_s^e	0.0025	0.0081	0.0402	–0.6398	4.0584	0.1056	–0.1234
Predictor variable							
I_{cpi}	0.0095	0.0077	0.0108	0.5673	2.7037	0.0362	–0.0079
ΔI_{cpi}	0.0001	0.0011	0.0158	–0.7709	3.2728	0.0247	–0.0432
I_{ppi}	0.0107	0.0134	0.0184	–0.8827	3.3025	0.0416	–0.0372
ΔI_{ppi}	0.0005	0.0014	0.0276	–0.8886	4.2916	0.0622	–0.0787

Panel B: Further statistics						
	Positive value			Negative value		
	Number of observations	Median	St. Dev.	Number of observations	Median	St. Dev.
Excess stock return						
R_s^e	59	0.0233	0.0217	41	–0.0238	0.0309
Predictor variable						
I_{cpi}	80	0.0103	0.0092	19	–0.0039	0.0018
ΔI_{cpi}	52	0.0112	0.0068	45	–0.0103	0.0122
I_{ppi}	78	0.0160	0.0095	22	–0.0163	0.0115
ΔI_{ppi}	55	0.0161	0.0141	45	–0.0114	0.0239

Notes: The sample period is from February 2002 through May 2010, and the sample contains 100 monthly observations. The variables are further divided into positive, zero and negative values in Panel B. For analysis, zeros values are not included.

Table 2 proceeds to provide estimation results of the correlation tests between the excess market returns and inflation variables, indicating the negative correlation coefficients for all of the inflation variables. It also highlights that only the coefficients on inflation variables measured by *PPI* were significant at the 1% level, suggesting that the predictor variables were closely correlated with the excess market returns, whereas this was not true for inflation variables measured by *CPI*.

Table 2
Correlation between excess market returns and inflation variables

Predictor variable	Pearson Correlation coefficient	Spearman Correlation coefficient	Number of observations
	$R^e_{s,t+1}$		
$I_{cpi,t}$	–0.2220 (0.0264) **	–0.1430 (0.1558)	100
$\Delta I_{cpi,t}$	–0.1398 (0.1654)	–0.1121 (0.2668)	100
$I_{ppi,t}$	–0.3081 (0.0018) ***	–0.4021 (0.0000) ***	100
$\Delta I_{ppi,t}$	–0.3113 (0.0016) ***	–0.4468 (0.0000) ***	100

Notes: The sample period is from February 2002 through May 2010, and the sample contains 100 monthly observations. *p values* are shown in parentheses. A significant relationship is assumed when both tests return *p* values less than 0.05. ** and *** indicate statistical significance at the 5% and the 1% levels, respectively.

On the one hand, the result of the significant relationship between inflation and stock market returns is broadly consistent with the findings derived using international financial market data (Adam, McQueen, & Wood, 2004; Fang et al., 2008). On the other hand, the different degree of correlation between inflation variables measured by *CPI* and *PPI* and the excess market returns is consistent with the asymmetric relationship between supply and demand in China (Chen, 2008). Specifically, the *CPI* is the weighted average of the prices of a set of consumer goods and services, whereas the *PPI* measures the average change in selling prices received by domestic producers of goods and services over time. In China, goods and services are in a buyers' market except for food, which is not fully supplied by the retail market, leading to a food-price-dominant *CPI*. By contrast, the government policy to invest in the market for a high growth of gross domestic product (GDP) increases the demand for industrial products and the amount of money available to investors. As a result, the *PPI* will surpass the *CPI* in terms of their impact on stock returns because of the asymmetric relationship between investment demand and retail demand.

Presence of Forecasting Ability

One primary question of interest within this paper concerns whether these inflation variables can be used to predict stock market downturns, which, by our definition, occur when the excess market returns are negative. The signalling power of inflation can be obtained by comparing the percentage of times when inflation provides correct signals with those when inflation provides incorrect signals. Figure 1 plots the excess market return levels and the signals from inflation variables.

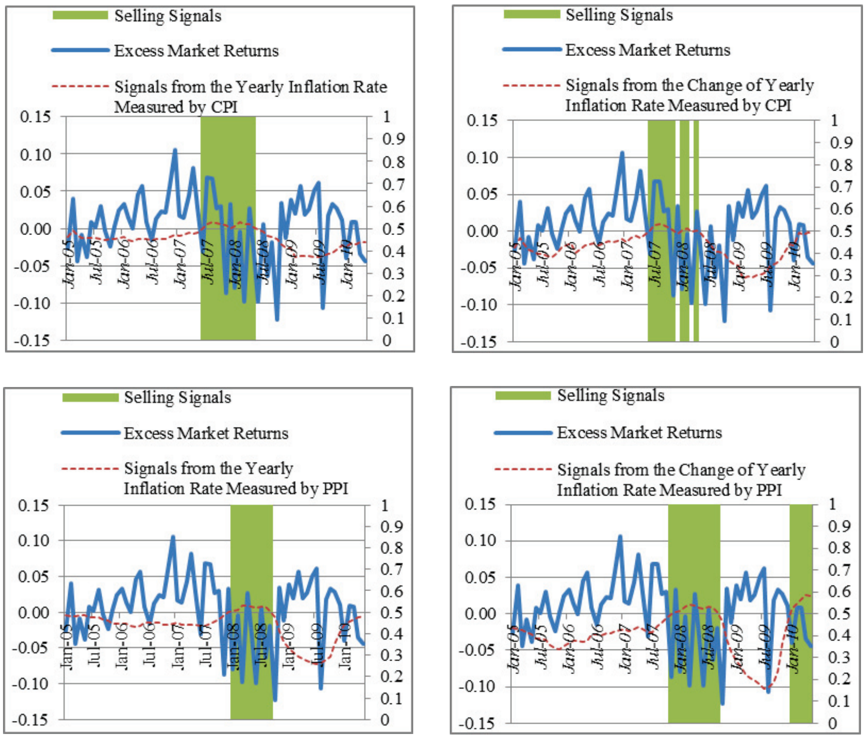


Figure 1. Excess market return levels and signals from inflation variables

As described before, the signals are constructed based on whether inflation variables exceed their pre-defined 90th percentile thresholds. When they extend beyond the thresholds, as shown by the positive values of the dashed line in the figure, an overpriced stock market and a resultant selling signal of stocks is identified. Otherwise, remaining in the stock market is preferred. As the first three years of data are used as the estimation period in calculating these thresholds, the actual testing is from January 2005.

It is of particular interest to study the ability of inflation variables to predict stock market downturns because these predictor variables more or less capture one of the most important market crashes in the history of Chinese stock markets, which occurred in October 2007. For example, the signals from the change of the yearly inflation rate measured by *PPI* identify the period from November 2007 to September 2008 as a period of market downturn, virtually timing the market collapse that took place in October 2007.

Table 3 further tabulates the predictions generated by the signals from each predictor variable. We first outline the notation used: $N_1(N_2)$ = the number of observations when the return on the stock market is smaller (larger) than the bond market; N = the total number of observations; $n_1(n_2)$ = the number of successful (unsuccessful) predictions when the return on the stock market is smaller (larger) than the bond market; n = the number of forecasts that the return on the stock market is smaller than the bond market.

Table 3
Predictions versus actual market performance

Predictor variable	Positive realised return	Negative realised return	Number of variable observations	Signal/number of observations
$I_{cpi,t}$	36	17	53	Signal of positive return
	$n_2 = 6$	$n_1 = 6$	12	Signal of negative return
	$N_2 = 42$	$N_1 = 23$	$N = 65$	Number of observations
$\Delta I_{cpi,t}$	37	19	56	Signal of positive return
	$n_2 = 5$	$n_1 = 4$	9	Signal of negative return
	$N_2 = 42$	$N_1 = 23$	$N = 65$	Number of observations
	40	16	56	Signal of positive return
$I_{ppi,t}$	$n_2 = 2$	$n_1 = 7$	9	Signal of negative return
	$N_2 = 42$	$N_1 = 23$	$N = 65$	Number of observations
$\Delta I_{ppi,t}$	37	12	49	Signal of positive return
	$n_2 = 5$	$n_1 = 11$	16	Signal of negative return
	$N_2 = 42$	$N_1 = 23$	$N = 65$	Number of observations

Note: The testing period is from January 2005 through May 2010, and the sample contains 65 monthly observations.

By our definition, market downturns (N_1 = 23) occurred for 35.38% of the months within the sample period (N = 65). When the signals from I_{ppi} (ΔI_{ppi}) predicted a market downturn, a market downturn indeed occurred in the next month 77.78% (68.75%) of the time. However, by contrast, a market downturn took place in 50% (44.44%) of the occasions when the signals from I_{cpi} (ΔI_{cpi}) predicted the same. The results indicate that the inflation variables measured by

PPI contain some useful information for predicting the vulnerability of the stock market in the near future.

We can formally test the statistical significance of the signals through the non-parametric method proposed by Henriksson and Merton (1981). The null hypothesis is that the signals from inflation generate accurate predictions randomly. More formally, the null hypothesis is that the sum of the ratio of successful forecasts $\frac{n_1}{N_1}+\left(1-\frac{n_2}{N_2}\right)$ has an expected value of unity. Under this null hypothesis, the number of forecasts that coincide with the actual market performance takes a hypergeometric distribution.

Table 4 reports the total number of observations (N), observations (N_1), forecasts (n), successful predictions (n_1) when the return on the stock market is smaller than the return on the bond market, and the sum of the ratio of successful predictions. Furthermore, it also reports the required value of the parameter to reject the null hypothesis, i.e., the signals contain no useful information at one-tail 99% and 95% confidence levels. For a given confidence level, the null hypothesis can be rejected if the number of successful predictions of market downturns n_1 is not less than the required value $\tilde{n}_1$.

Table 4
Henriksson and Merton Test on the significance of inflation signals

Predictor variable	N	N_1	n	n_1	Required value of $\tilde{n}_t$	Significance level	$\frac{n_1}{N_1}+(1-\frac{n_2}{N_2})$
$I_{cpi,t}$	65	23	12	6	8	1%	1.1180
	65	23	12	6	7	5%	
$\Delta I_{cpi,t}$	65	23	9	4	6	1%	1.1263
	65	23	9	4	5	5%	
$I_{ppi,t}$	65	23	9	7	6	1%	1.2567
$\Delta I_{ppi,t}$	65	23	16	11	10	1%	1.3593

Notes: The testing period is from January 2005 through May 2010, and the sample contains 65 monthly observations. ** and *** indicate statistical significance at the 5% and the 1% levels, respectively.

The statistics presented in Table 4 point to the ability of inflation variables measured by *PPI* to predict market downturns, with the signals from I_{ppi} (ΔI_{ppi}) predicting 9 (16) market downturns with 77.78% (68.755) accuracy. The sum of the conditional probability of successful forecasts $\frac{n_1}{N_1}+\left(1-\frac{n_2}{N_2}\right)$ is 1.2567 (1.3593). Importantly, the number of successful predictions n_1 is not less than the require value of $\tilde{n}_1$. The null hypothesis can therefore be rejected at the 1%

level of statistical significance. By contrast, the signals from I_{cpi} (ΔI_{cpi}) predicted 12 (9) market downturns with 50% (44.44%) accuracy, with the sum of the conditional probability of successful forecasts being 1.1180 (1.1263). The number of successful predictions n_1 is less than the required value of $\tilde{n}_1$. Therefore, the null hypothesis that the signals produce accurate predictions randomly cannot be rejected.

We also test whether the signals from the inflation variables are able to identify large market downturns as a robustness check. Table 5 presents some statistical evidence concerning whether the excess stock market performed very differently when the variables exceeded their 90th percentile thresholds. The last row of the table shows that for the entire testing period of 65 months, the monthly total returns of the excess stock market averaged 0.48% with a median of 1.44%.

Table 5
Market performance and signals from inflation variables

Predictor variable	Signal from predictor variable	Mean of excess market return	Median of excess market return	St. Dev. of excess market return
$I_{cpi,t}$	<90th percentile (stay)	0.0074	0.0144	0.0438
	>90th percentile (sell)	–0.0065	0.0116	0.0585
		(0.1860)	(0.4170)	(0.1110)
$\Delta I_{cpi,t}$	<90th percentile (stay)	0.0053	0.0132	0.0453
	>90th percentile (sell)	0.0021	0.0268	0.0575
		(0.3840)	(0.8370)	(0.1810)
$I_{ppi,t}$	<90th percentile (stay)	0.0121	0.0188	0.0428
	>90th percentile (sell)	–0.0401	–0.0318	0.0466
		(0.0030)***	(0.0080) ***	(0.3600)
$\Delta I_{ppi,t}$	<90th percentile (stay)	0.0170	0.0212	0.0412
	>90th percentile (sell)	–0.0322	–0.0331	0.0437
		(0.0000)***	(0.0010) ***	(0.3960)
Testing period		0.0048	0.0144	0.0467

Notes: The testing period is from January 2005 through May 2010, and the sample contains 65 monthly observations. *p*-values in parentheses are estimated using Monte Carlo simulations. ** and *** indicate statistical significance at the 5% and the 1% levels, respectively.

The other rows compare the market performance after the months when inflation variables exceeded their 90th percentile thresholds and other months. It shows the ability of the signals from inflation variables measured by *PPI* to capture large market downturns: for the 12 (9) months when I_{cpi} (ΔI_{cpi}) exceeded its 90th percentile threshold, the excess market returns averaged –0.65% (0.21%). For the other 53 (56) months, however, the returns averaged 0.74% (0.53%), and the difference in these returns was not statistically significant. By contrast, the results are completely different when the signals from I_{ppi} (ΔI_{ppi}) are considered. The average excess market return of –4.01% (–3.22%) for the months when I_{ppi} (ΔI_{ppi}) exceeded the 90th percentile threshold was considerably lower than that of 1.21% (1.70%) for other months, with the difference being significant at the 1% statistical level.

The abovementioned results suggest a poor performance of the stock market after the months when inflation variables, measured by *PPI*, exceeded their 90th percentile thresholds, both in terms of the mean and median. However, the central question in interpreting the evidence concerns whether the statistical significance also leads to the economic value. Therefore, we test this hypothesis below.

Market-Timing Activity

We formulate market-timing strategies based on the signals from the inflation variables to test the economic value of the predictability of stock market downturns. Historical data are used to compare the performance of the market-timing portfolios with the benchmark portfolio, a 100% stock portfolio. Table 6 reports the statistics for both the market-timing portfolios and the benchmark portfolio, assuming an initial wealth of $ 100 invested in the market index at the end of January 2005. We do not make any assumptions about the distribution of portfolio returns and choose to report traditional metrics, including the Sharpe Ratio and Jensen's Alpha for normal distributions and the Omega Ratios specifically for non-normal distributions. The risk-free rate is represented by the 3-month time deposit rate converted to a monthly basis. Strategy profitability is designated when all of these statistics return the same indication in support of or against the superiority of market-timing strategies to the benchmark. The stock index return is used as the market proxy to calculate Jensen's Alpha, whereas the risk-free rate is taken as the target rate to derive the Omega Ratio.

The results presented below are broadly in line with those presented earlier. Before transaction costs, the performance of the market-timing portfolios using the signals from I_{ppi} (ΔI_{ppi}) is superior to the benchmark portfolio in terms of all statistics. However, this is not the case for the signals from ΔI_{cpi}. The reliability of I_{cpi} is also open to questioning as a result of the difficulty in implementing a corresponding market-timing strategy: the monthly average return of the portfolio is less than the risk-free rate, which results in a negative Sharpe Ratio, indicating an unappealing risk-adjusted return. The Jensen's Alpha (–0.02% per month or –0.24% per year) shows no abnormal return over the theoretical expected return. Furthermore, the Omega Ratio, which is calculated as the probability weighted ratio of gains to losses relative to the threshold (the three-month deposit rate), is less than 1, also indicating low levels of profitability from the strategy.

Li and Lam (2002) emphasise that evaluating the effect of transaction costs represents an important issue concerning a trading strategy's success. As shown by the shaded areas in Figure 1, the signals from the inflation variables do not involve much trading: those from ΔI_{cpi}, which triggered the largest number of transactions among all the variables, only made 3 round-trip trades or 6 actual trades during the period of 65 months.

Table 6
Market-timing portfolios versus the benchmark portfolio

Strategy	Number of observations	Mean	St. Dev.	Sharpe Ratio	Jensen's Alpha	Omega Ratio	Final portfolio value
			No transaction costs				
$I_{cpi,t}$	65	0.0052	0.0400	–0.0440	–0.0002	0.7720	140.0433
$\Delta I_{cpi,t}$	65	0.0036	0.0426	–0.0789	–0.0016	0.7069	126.3532
$I_{ppi,t}$	65	0.0095	0.0402	0.0632	0.0042	1.0649	185.3902
$\Delta I_{ppi,t}$	65	0.0120	0.0366	0.1377	0.0065	1.3172	217.9110
Benchmark	65	0.0037	0.0473	–0.0689	–0.0011	0.7496	127.0193
			1% transaction costs				
$I_{cpi,t}$	65	0.0049	0.0405	–0.0509	–0.0005	0.7561	137.2565
$\Delta I_{cpi,t}$	65	0.0027	0.0431	–0.0988	–0.0025	0.6682	118.9591
$I_{ppi,t}$	65	0.0092	0.0408	0.0549	0.0039	1.0361	181.7010
$\Delta I_{ppi,t}$	65	0.0115	0.0373	0.1222	0.0060	1.2543	211.4388
Benchmark	65	0.0037	0.0473	–0.0689	–0.0011	0.7496	127.0193

Note: The testing period is from January 2005 through May 2010, and the sample contains 65 monthly observations.

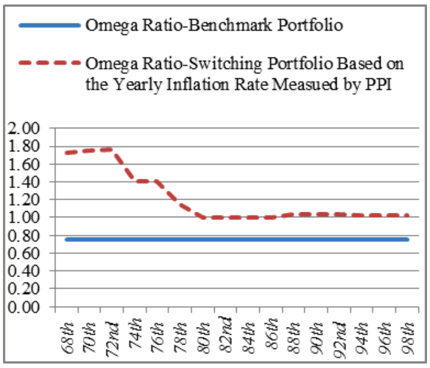
Given that the market-timing strategies did not require frequent switches between the markets, the inclusion of transaction costs has a very limited effect on the results, with the market-timing portfolios using inflation variables measured by *PPI* continuing to work well: after 1% transaction costs, the monthly average return generated by the market-timing strategy using I_{ppi} (ΔI_{ppi}) is 0.92% (1.15%) or 11.67% (14.805) per year. By contrast, the monthly average return from holding the market is only 0.37% (4.54% per year). For example, \$ 100 invested at the beginning of January 2005 would become approximately \$ 127.0193 at the end of May 2010 if it remains in the stock market for the entire period. However, the wealth would rise to \$ 181.7010 (\$ 211.4388) using our I_{ppi} (ΔI_{ppi})-based strategy. The Jensen's Alpha of 0.39% (0.60%) per month indicates a significant amount of abnormal return of the market-timing portfolio over the theoretical expected return. This is also supported by the Omega Ratio.

Sensitivity Analysis

Questions might naturally arise regarding the extent to which the results in Table 6 depend on the particular parameter or model specifications used. Accordingly, we present a sensitivity analysis to evaluate the robustness of the market-timing strategies based on the signals from inflation variables measured by *PPI*. We use the Omega Ratio, calculated under transaction costs of 1% of the traded portfolio value, in the sensitivity analysis tests, given that there is a high likelihood of non-normal return distributions in a sample of 65 observations.

Possible misgivings might be raised regarding the percentile threshold chosen for the forecasting model, given that it is not theoretically motivated and therefore represents an arbitrary parameter. Figure 2 shows the Omega Ratios of the market-timing portfolios using inflation variables measured by *PPI* and the benchmark portfolio, depending on the different choices of the percentiles from the 68th to the 98th. It is apparent that the Omega Rations are higher for both market-timing portfolios than for the benchmark for every percentile, with values above 1 translating as a probability that gains exceed losses.

We also modify the stock market index given that there is no *a priori* reason to indicate the correct choice of an index. Table 7 examines the two other main stock market benchmarks in China, namely the *SHC* and the *SZC*, with the main observation as follows: both market-timing portfolios using inflation variables measured by *PPI* outperform the benchmark portfolio, irrespective of the stock market index chosen. Therefore, this indicates that our market-timing strategies work in the Chinese stock market irrespective of the index chosen.



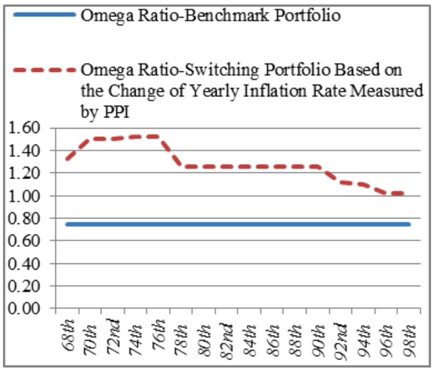


Figure 2. Market-timing portfolios versus the benchmark portfolio-modifying percentile thresholds

Table 7
Market timing portfolios versus the benchmark portfolio – modifying the stock market index

Strategy	Stock index	Omega ratio	Number of observations
	1% transaction costs		
I_{ppi}		1.0373	65
ΔI_{ppi}	SHC	1.2536	65
Benchmark		0.7705	65
	1% transaction costs		
I_{ppi}		1.2586	65
ΔI_{ppi}	SZC	1.3919	65
Benchmark		0.9012	65

Note: The testing period is from January 2005 to May 2010, and the sample contains 65 monthly observations.

The abovementioned results suggest the outperformance of the market-timing strategies using inflation variables measured by *PPI* over the benchmark in terms of both the traditional metrics and the Omega Ratio. Particularly, the superiority of inflation variables measured by *PPI* to *CPI* on forecasting market downturns is consistent with the correlation analysis presented in Table 2. Therefore, the results generally support previous studies in that inflation plays an important role in explaining stock returns. They also support two hypotheses regarding the Chinese stock market: (1) fundamentals are potential pricing factors (Bondt, Peltonen, & Santabarbara, 2011); and (2) market prices do not fully incorporate all publicly available information (Su, 2003; Gao & Tse, 2004). These insights therefore provide evidence against previous studies arguing that Chinese stock prices are mainly driven by sentiment (Girardin & Liu, 2003; Tan, Chiang, Mason, & Nelling, 2008). Conversely, the market participants' responses are in accordance with widely accepted views concerning how the economy operates, with investors able to trade on the basis of inflation-related information.

Time-varying Investment Opportunities

Given the time-varying investment opportunities found in international markets (Paye & Timmermann, 2006), a natural question to ask is whether it also occurs in Chinese financial markets. Accordingly, we investigate this by modifying the forecasting window size: besides the fixed rolling window method presented earlier, we also consider an expanding window method by only adding a new observation each time to update the threshold and assess the presence and the importance of time variations by comparing the profitability of market-timing strategies using two different methodological perspectives, as suggested by Pesaran and Timmermann (2002).

Table 8 shows that accurate market downturn predictions n_1 for both the rolling and the expanding windows are generally close to each other on average. However, there is one exception: the signals from ΔI_{ppi} using the fixed rolling window produced 11 accurate market downturn predictions compared to just 6 using the expanding window. Furthermore, the identification of market downturns using the fixed rolling window clustered over the periods November 2007 to September 2008 and January 2010 to May 2010 contrast with the periods May 2008 to September 2008 and January 2010 to May 2010, as predicted under the expanding window. Estimating the direction of the market using the local maxima of the sample path of stock index prices, we find three major peaks: February 2005, October 2007 and July 2009. Given that the fixed rolling window is more successful in identifying breaks in the prediction models, it was able to capture market downturns more quickly than the expanding window.

The findings suggest that the ability of ΔI_{ppi} to predict market downturns underwent important breaks over the period. To investigate the effect of model instability on economic value, Table 8 further compares the profitability of the market-timing strategies inclusive of transaction costs of 1% of the traded portfolio value.

Table 8
Market-timing portfolios versus the benchmark portfolio – the expanding window method versus the fixed rolling method

Strategy	Accurate market downturns	Sharpe Ratio	Jensen's Alpha	Omega Ratio
$I_{cpi,t}$	7/13	–0.0130	–0.000	0.8521
	(6/12)	(–0.0509)	(–0.0005)	(0.7561)
$\Delta I_{cpi,t}$	4/9	–0.0706	–0.0012	0.7248
	4/9	(–0.0988)	(–0.0025)	(0.6682)
$I_{ppi,t}$	6/8	0.0255	0.0027	0.9509
	(7/9)	(0.0549)	(0.0039)	(1.0361)
$\Delta I_{ppi,t}$	6/9	0.0197	0.0027	0.9504
	(11/16)	(0.1222)	(0.0060)	(1.2543)
Benchmark	N.A	–0.0689	–0.0011	0.7496

Notes: The testing period is from January 2005 to May 2010, and the sample contains 65 monthly observations. The results of using the fixed rolling window are in parenthesis.

As expected, the profitability of the strategies is similar on average under the two methods except when using ΔI_{ppi}. While one would expect the predictions generated by the expanding window to deliver better performance if there were no breaks, the economic value of the market-timing strategy using this method is relatively low. For example, as denoted by Jensen's Alpha, the abnormal return of the market-timing portfolio over the theoretical expected return is only 0.27% per month (3.28% per year), in contrast to 0.60% per month (7.47% per year) under the rolling method. The Omega Ratio 0.9504 suggests a lower probability of gains than losses.

The results reinforce the existence of shifts in the forecasting ability of ΔI_{ppi} over the study period.

Our findings bring into question the common practice of assuming a stable prediction model for asset returns and its impact on asset allocation decisions. If the relationships between asset returns and macroeconomic variables such as ΔI_{ppi} undergo unexpected structural breaks, this practice would lead to incorrect predictions of market performance. In terms of asset allocation practice, this suggests that it may be advisable to hedge against the possibility of a break in the relationships over time.

CONCLUSIONS AND IMPLICATIONS

This study examines whether the predictable patterns in the Chinese stock market can be exploited using measures of inflation to formulate market-timing strategies. Such statements have implications for both investors and policymakers, with investors being potentially able to benefit from successful market-timing strategies, whereas policymakers can make more informed decisions with regard to their policies.

Particularly, we have investigated four market-timing strategies using the yearly inflation rates and the changes of the yearly inflation rates as measured by *CPI* and *PPI*. All the strategies require investing in the stock market index unless a pre-defined threshold is exceeded.

Our results show that the market-timing strategies using inflation variables measured by *PPI* robustly outperform the benchmark buy-and-hold strategy even after transaction costs. The superior forecasting ability of inflation variables measured by *PPI* to *CPI* is expected and consistent with the asymmetric relationship between supply and demand in China. Our work thus provides evidence in support of using a simple rule of thumb strategy to avoid some market downturns and enhance returns over those from the widely recommended buy-and-hold strategy.

However, one factor that must be kept in mind is that investors must be aware of time variations, particularly when using macroeconomic variables to time the market. As shown in the paper, the forecasts generated by the signals from ΔI_{ppi} contain completely different information concerning stock market downturns at various times during the study period, providing new evidence of the time-varying investment opportunities in the Chinese stock market. The consequent impact on the profitability of the market-timing strategy suggests that it may be advisable to hedge against the possibility of a break in the relationship over time when making asset allocation decisions.

Overall, the results of this study support the idea that investors are able to time the stock market on the basis of inflation-related information and highlight the potential time-varying investment opportunities in the Chinese stock market.

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