Fundamental Analysis versus Technical Analysis: Which Matters More?

Leon Li
Associate Professor of Finance
Subject Convenor, Finance
Waikato Management School
University of Waikato, New Zealand
Phone Number: +64-7-858-5650
E-mail: leonli@waikato.ac.nz

September 2019

Fundamental Analysis versus Technical Analysis: Which Matters More?

ABSTRACT

Whether fundamental analysis or technical analysis should be employed to predict stock returns is a longstanding debate in the literature. Incorporating a regime-switching mechanism, we establish a hybrid model with non-uniform weightings on each type of analysis to examine the debate. Our empirical results are consistent with the following notions. First, stock investors should give more weight to fundamental analysis for firms with incremental information involved in accounting reporting proxied by discretionary accruals. Second, for firms with high dispersion in financial analysts' forecasts, stock returns are more influenced by accounting data, which implies that stock investors care more about the intrinsic value of firms obtained with fundamental analysis when encountering information asymmetry or uncertainty. Third, the weight given to fundamental analysis should be increased for stocks with unusual volatility in prices. However, when the market is crashing, fundamental analysis might become invalid, and thus the weighting given to fundamental analysis should be decreased. For technical analysis, the reverse of these arguments holds true. The results are robust to alternative measures of the variables.

JEL classification: G33, C51

Keywords: Regime-switching system; fundamental analysis; technical analysis; earnings management; information asymmetry

Data Availability: From the sources identified in this paper

1. Introduction

The research issues of this study relate to stock return prediction. This study differs from previous studies by offering a novel perspective on how stock returns and the two types of analysis, fundamental and technical analysis, are related. We contend that, regardless of whether a trading strategy is found to be superior to another, the other should not be neglected entirely. We argue that the weight given to each type of approach should not be constant across stocks and over time. This work offers a novel perspective on how stock returns and the two types of analysis are related. We develop several testable hypotheses and adopt the regime-switching framework to test these hypotheses using the realized data.

The approaches to predict stock returns can be broadly grouped into two categories: fundamental analysis and technical analysis. The former seeks to predict stock returns based on a set of accounting-based ratios (e.g., Oppenheimer and Schlarbaum, 1981; Fama and French, 1992; Lakonishok et al., 1994; Davis, 1994; Metghalchi et al., 2008). The latter predicts stock returns based on past market data, i.e., past stock returns and trading volume (e.g., Lee and Swaminathan, 2000; Llorente et al., 2002; Park and Irwin, 2007; Zhu and Zhou, 2009; Wei et al., 2011; Yamamoto, 2012). Whether the fundamental or technical approach should be employed to predict stock returns is a longstanding debate in the literature (e.g., Lo et al., 2000; Nazário et al., 2017; Avramov et al., 2018). We argue that investors, in practice, incorporate different sources of information involved in the two types of analyses in arriving at their investment decision and rarely opt for only one approach.

The aim of this study is to consider the potential of combining the two alternative analyses into a hybrid model and to investigate the optimal *weighting* given to the two types of information (i.e., accounting data versus market data). In brief, this study posits that the weighting should not be constant across stocks and over time and thus address a critical question: When should stock investors pay more attention to the information of accounting data or market data? To the best of our knowledge, few, if any, prior studies have explored this critical issue in relation to stock return prediction.

This study employs a regime-switching approach to establish a hybrid model with non-monotonic weightings on the two types of information. In particular, we establish a framework in which two states are defined for capturing two different stock return prediction alternatives, i.e., fundamental analysis and technical analysis. Moreover, one key feature of our model is its estimation of the probabilities of the specific state at each firm and time by using the data themselves. This study thus adopts this estimated dynamic probability to serve as a means of determining the weighting of each forecasting technique.

We use the three accounting-based ratios suggested by Dechow, et al. (2001) to develop the fundamental analysis for stock return prediction. Next, past stock return and trading volume are employed to establish the approach of technical analysis. Finally, we address and test four variables which could be related to the non-monotonic weighting on each analysis, including return volatility, discretionary accounting accruals, dispersion in financial analysts' forecasts, and a market crisis dummy. Our sample consists of 31,469 U.S. firm-year observations for 5,678 unique firms from 1996–2015.

We find all of the accounting-based and market-based variables to be statistically significant, which is consistent with the literature. The results obtained with our hybrid model further show that the weighting for the technical analysis is negatively related to discretionary accounting accruals and dispersion in financial analysts' forecasts but is positively related to the market crisis dummy. The opposite is true for fundamental analysis. Moreover, we show that the high and low volatility state correspond to the forecasting technique of fundamental and technical analysis, respectively. This finding implies that stock investors give more weighting to fundamental analysis for stocks with volatile prices.

Overall, our results show that the weighting given to each forecasting approach (fundamental analysis versus technical analysis) is not uniform across stocks and over time. More specifically, investors give more weighting to fundamental analysis when considering firms with incremental information involved in their accounting reporting, when there is a high degree of uncertainty (or information asymmetry), and when stock price is volatile. However, during a period of market crisis, stock investors may be swamped by panic, which would adversely affect their ability to value stocks efficiently. Accordingly, the weight given to fundamental analysis should be decreased. The reverse of these arguments is true for technical analysis.

Our study contributes to the literature in several ways. First, we employ a method that recognizes differences in the importance of the accounting- and market-based variables in stock return prediction and we develop a hybrid model with endogenous and non-monotonic weightings in each approach to produce results that cannot be observed under the traditional linear model. Second, some recent studies have employed intelligent system techniques, such as neural networks and fuzzy systems, to examine the nonlinear feature of stock markets (see Vanstone and Finnie, 2009; Bisoi and Dash, 2014; Wei et al., 2011; Ticknor, 2013; Kazem et al., 2013). However, we argue that those studies fail to clearly demonstrate the relative importance of fundamental analysis against technical analysis. The continuous and smooth probability design established in this study essentially mitigates this limitation. Accordingly, our study provides evidence that helps to resolve the debate in prior research concerning the relative importance of fundamental analysis versus technical analysis. Third, our study contributes to the literature on accounting accruals and analysts' forecast dispersion -- two important research topics in finance and accounting. Prior studies have shown the relation between stock returns and accounting accruals (e.g., Myers et al., 2007; Dechow et al., 2010) and the connection between stock returns and analysts' forecast dispersion (e.g., Diether et al., 2002; Johnson, 2004). We establish a link between this body of literature and the choice between fundamental analysis and technical analysis.

The rest of the paper is organized as follows. Section 2 reviews related studies and develops the research questions. Section 3 discusses the model specifications and demonstrates that the hybrid model with non-monotonic weightings is an appropriate method for our study. Section 4 describes the data and measurement of the variables. Section 5 presents the empirical results. Finally, Section 6 concludes the investigation and identifies several directions for future research.

2. Related studies and research questions

2.1 Studies on fundamental analysis and technical analysis

Finding valuable information that affects stock returns is an important research issue in practice and academia. Most finance researchers agree that the fundamental analysis approach, based on accounting-based ratios, could help predict future stock (e.g., Basu, 1977; Rosenberg et al., 1985; Jaffe et al., 1989; Chan et al., 1991; Fama and French, 1992; Lakonishok et al., 1994; Davis, 1994; Ohlson, 1995; Frankel and Lee, 1998; Dechow et al., 1999). Fundamental analysis holds that these accounting ratios present the intrinsic value of the firm and investors may compare the intrinsic values based on accounting data with the observed market prices to make an investment decision.

However, market investors also carefully watch market data, namely, past stock returns and trading volume. Investors study the past market data to predict future stock returns, all of which constitutes technical analysis. A large body of evidence demonstrates that technical analysis is useful to predict future stock returns (e.g., Lee and Swaminathan, 200l; Llorente et al., 2002; Park and Irwin, 2007; Chavarnakul and Enke, 2009; Zhu and Zhou, 2009; Teixeira and Oliveira, 2010; Yamamoto, 2012). The concept of technical analysis is that information contained in market prices and trading volume of security could be incompletely reflected in current stock prices. Therefore, it would be possible to earn an abnormal return by looking for patterns in stock prices and trading volume. The advantage of market data over accounting data is that market data could reflect a considerable number of external factors which might affect stock prices, such as political events, market news, international influence, and trading behavior.

The question of whether fundamental analysis or technical analysis should be employed to predict stock returns is longstanding in the finance research fields (see Brock et al., 1992; Lo et al., 2000; Menkhoff and Taylor, 2007; Vanstone and Finnie, 2009; Park and Irwin, 2009; Menkhoff, 2010; Mitra, 2011; Zhu and Zhou, 2009; Nazário et al., 2017). We argue that even if one analysis is superior to the other, this does not imply that the inferior analysis should be neglected altogether, and in fact, it may be possible to combine them to form an even better method. Moreover, both accounting ratios and market data should be valuable for stock return prediction. This study thus establishes a hybrid model in which both types of information are considered and utilized simultaneously in predicting future stock returns. In brief, we define a two-state system controlled by the state variable: Regime I is set where stock returns depend on market data, while regime II is set when we use accounting ratios to predict stock returns. To control the dynamic process of the state variable, we use the logistic function to develop the probability of state ranging from zero to one, and conditional on several information variables, such as incremental information involved in accounting figures, information asymmetry (or uncertainty) and market crisis condition. It should be noted that the probabilities of a specific state for a certain stock at any given time period are estimated by the data themselves. Then we apply the estimated probabilities to serve as the weightings for each technique.

In addition to a new methodological approach, this research makes theoretical contributions by addressing several testable hypotheses regarding the debate of fundamental analysis versus technical analysis. In brief, we hypothesize that investors should adjust the weight they give to fundamental analysis and/or technical analysis under certain conditions. Our results offer new insights into the longstanding debate of fundamental analysis versus technical analysis. In the following section, we detail the development of our theoretical hypotheses.

2.2 Development of research hypotheses

This study departs from previous studies by offering a new perspective on the choice between fundamental analysis and technical analysis and it explores the effectiveness of a hybrid model that incorporates information from both methods. This issue merits detailed study because both accounting- and market-based data should be valuable for investors in markets. Moreover, stock investors could weigh accounting data more heavily in some conditions or times and rely more on market data in others.

We propose that even if one forecast model is superior to another, it does not follow that the lesser model should be neglected altogether. In practice, investors rarely opt for only one approach and might consider different sources of information when arriving at an investment decision. We focus on determining the optimal weighting for each type of information when they are incorporated into the hybrid model. In particular, we contend the weighting is not monotonic and address four research hypotheses as follows.

Fundamental analysis involves comparing the estimates of intrinsic values based on accounting data to observed market prices. If the observed price is too high compared to the intrinsic value, investors will sell the stock, which causes the former to decrease to return the equilibrium of price and value. On the other hand, if the observed price is too low compared to the intrinsic value, investors will buy the stock, which causes the former to increase to return to the equilibrium of price and value. With regard to nonlinear adjustment, the speed of convergence toward intrinsic values based on fundamental analysis would be expected to increase as the deviation from intrinsic values rises in absolute value. Moreover, because intrinsic values are relatively stable, the increased deviation from intrinsic values should closely associate with the high volatility in observed stock prices. The opposite is true for stocks with low volatility in prices. Accordingly, we expect to observe a positive association between return volatility and fundamental analysis. The opposite is true for technical analysis. Based on this reasoning, we establish our first hypothesis as follows:

H1: Fundamental analysis and technical analysis correspond to the state of high and low volatility, respectively.

As the literature clearly shows, earnings management is prevalent among business organizations (Graham et al., 2005). Earnings management by corporate managers is due to inherent flexibility in generally accepted accounting principles (GAAP). Accounting discretions embedded in GAAP offer opportunities for corporate managers to adjust income numbers (either upward or downward). The mainstream in accounting literature propones that managers could use discretionary accruals to improve the quality of reported earnings by communicating proprietary information to market participants. Healy and Palepu (1993) indicate that corporate executives incorporate impact from current economic events and private information into current-period earnings as much as possible. To achieve this objective, managers can leverage discretionary accruals to reveal their private knowledge to market participants, even when capital markets have been considered efficient. Following the study of Healy and Palepu (1993), many researchers show evidence supporting earnings management, because such a strategy strengthens communications between firm management and corporate outsiders (e.g., Dechow and Skinner, 2000; Sankar and Subramanyam, 2001; Krishnan, 2003; Tucker and Zarowin, 2006; Hann et al., 2007).

On the other hand, a few researchers point out that managers might use their discretion and report earnings opportunistically to maximize their own utility (e.g., Burgstahler and Dichev, 1997; Balsam et al., 2002; Burgstahler and Eames, 2006). Accordingly, discretionary accruals by managers could damage financial reporting quality. Therefore, the literature defines two different types of earnings management: efficient and opportunistic earnings management (Scott, 2000).

This study links the issue of earnings management with the choice between fundamental analysis and technical analysis. We argue that if earnings management is efficient, then discretionary accruals (earnings management proxy) have a positive relationship with the weight given to fundamental analysis. If, on the other hand, earnings management is opportunistic, the relationship is negative. Since the relationship can go either way -- positive if earnings management is efficient and negative if opportunistic -- the hypothesis is non-directional:

H2: There is a relationship between discretionary accruals and the weightings given to fundamental analysis versus technical analysis.

Analysts’ forecast dispersion measures the disagreement among analysts with regard to the expected earnings of a given firm. Diether et al. (2002) consider dispersion in analysts’ earnings forecasts as a measure of information asymmetry. Johnson (2004) uses it to measure the degree of uncertainty. Plenty of studies have further addressed and tested the relation between stock returns and dispersion in analysts’ earnings forecasts (e.g., Garfinkel and Sokobin, 2006; Garfinkel, 2009; Barron et al., 2009). In this study, we bridge the issue of analysts’ forecast dispersion and the choice between fundamental analysis and technical analysis. From the standpoint of risk aversion, we argue that market investors could become defensive and be more concerned about the intrinsic value obtained with fundamental analysis when the firms in which they have invested are associated with a high degree of information asymmetry or uncertainty. Investors would act in a more fundamentalist manner and thus give greater weighting to fundamental analysis. Following this argument, our third hypothesis is presented below:

H3: The weighting given to fundamental analysis and technical analysis is positively and negatively related to the level of information asymmetry (or uncertainty), respectively.

Our final hypothesis relates to the condition of the market crisis. Fundamental analysis literature assumes that investors could estimate the intrinsic (or fair) value of shares using valuation models by fundamental analysis. However, we argue that stock investors could be swamped by panic in a chaotic financial environment, which would adversely affect their ability to value stocks efficiently (e.g., Hoque et al., 2007; Kim and Shamsuddin, 2008; Lim et al., 2008). Moreover, the information in financial statements suffers from release delays and thus becomes less useful for decision-making by market participants. On the other hand, the market data in the technical analysis could quickly reflect the updated information. Based on this logic, we establish the fourth hypothesis:

H4: The weighting given to fundamental analysis and technical analysis is negatively and positively related to the occurrence of a market crisis, respectively.

In concluding the discussion so far, the aim of this study is to investigate whether (and how) the weight given to fundamental analysis and technical analysis is influenced by the four variables -- stock return volatility, discretionary accruals, analysts' forecast dispersion, and crisis occurrence -- and develop four corresponding hypotheses. To test these hypotheses, this investigation develops a hybrid model associated with non-monotonic weightings on fundamental analysis and technical analysis. In the next section, we discuss the problems of conventional approaches and demonstrate why a hybrid model with non-monotonic weightings on fundamental analysis and technical analysis could provide an appropriate solution to these problems.

3. Model specifications

3.1 Technical analysis (Model 1)

This work adopts past market data, including stock return and trading volume, to model the technical analysis. The setting of technical analysis is presented as follows:

$$RET_{i,t+1q} = const. + \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t} + u_{i,t}, \qquad u_{i,t} \sim N(0,\sigma), \tag{1}$$

where the explanatory variables $PRET_{i,t}$ and $PVOL_{i,t}$, $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots, T$, represent past stock return and trading volume of the stock, where the subscript *i* denotes the *i*-th stock and *t* denotes the *t*-th year. The explained variable $RET_{i,t+1q}$ is the subsequent quarterly stock return. The $u_{i,t}$ represents the residual term in the regression and follows the Gaussian distribution with standard error σ. Although the best technical analysis model for stock return can be determined, it is not the purpose of this study. The simple setting is adopted for reasons of convenience.

3.2 Fundamental analysis (Model 2)

The technical analysis described above relies mostly on information obtained from market data, including return and volume. A contrasting approach is the fundamental analysis method based on accounting data. Following Patricia et al. (2001), three accounting-based ratios are adopted to develop the fundamental analysis in this study:

$$RET_{i,t+1q} = const. + \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t} + u_{i,t}, \qquad u_{i,t} \sim N(0,\sigma). \tag{2}$$

In the above setting, *CF/P* represents the cash-flow-to-price ratio (see Basu, 1983; Lakonishok et al., 1994; Sloan 1996), *E/P* is the earnings-to-price ratio (see Basu, 1983; Fama and French, 1992) and *B/M* is the book-to-market ratio (see Stattman, 1980; Rosenberg et al., 1985; Fama and French, 1992).

3.3 Hybrid stock return prediction model via the conventional regression (Model 3)

Data for both the technical analysis and fundamental analysis could be captured by introducing a method that consists of a specification that includes all the explanatory variables appearing in both forecasting approaches. The following model specification is thus established:

$$RET_{i,t+1q} = const. + \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t} \\ + \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t} \\ + u_{i,t}, \quad u_{i,t} \sim N(0,\sigma). \tag{3}$$

This regression analysis includes the two market variables and the three accounting ratios as the explanatory variables for the subsequent quarterly stock return. We label the regression as Model 3. Notably, there are two key limitations in Model 3. First, Model 3 assumes single return volatility, i.e., σ. Therefore, the model is incapable of testing the relationship between return volatility and the two types of analysis, as addressed in our H1. Second, Model 3 is unable to explicitly identify the weight given to each type of analysis.

3.4 Hybrid stock return prediction model via the regime-switching system (Models 4 and 5)

To mitigate the problems of Model 3, we employ a state-varying system to establish the following model specification:

$$RET_{i,t+1q} = \begin{cases} const_1 + \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t} + u_{i,t}, \quad u_{i,t} \sim N(0,\sigma_1) \quad if \quad s_{i,t} = 1 \\ \\ const_2 + \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t} + u_{i,t} \quad , \\ \quad u_{i,t} \sim N(0,\sigma_2) \quad if \quad s_{i,t} = 2, \end{cases} \tag{4}$$

Notably, $s_{i,t}$ is a state variable and a two-state system is defined in Equation (4): regime I (namely, $s_{i,t} = 1$) is set where the subsequent quarterly stock return (i.e., $RET_{i,t+1q}$) depends on the two market variables in the technical analysis, while regime II (namely, $s_{i,t} = 2$) is set when we use the three accounting ratios in the fundamental analysis to explain the subsequent stock return. Next, to identify the weight for each type of analysis, we use the logistic function to define the probability of each state:

$$w = prob(s_{i,t} = 1) = \frac{\exp(\theta_0)}{1 + \exp(\theta_0)}, \quad prob(s_{i,t} = 2) = 1 - w\,. \tag{5}$$

The above specification is labeled as Model 4. Compared with Model 3, there are two advantages in Model 4. First, two measures for the standard errors are designated: σ_1 and σ_2, for capturing the dynamics of return volatility. This setting helps detect our H1, the relationship between return volatility and the two types of analysis. The following question arises: Do market investors give greater weight to fundamental analysis or technical analysis for stocks with volatile prices? Second, using the regime-switching framework, we may clearly estimate the weight for each type of analysis, i.e., w for technical analysis and ($1 - w$) for fundamental analysis. Moreover, Equation (1) for the technical analysis and Equation (2) for the fundamental analysis are two special cases of Model 4 under the restriction of $w = 1$ and $w = 0$, respectively.

To test our H2, H3, and H4, we improve Equation (5) by making the probability of state conditional on three information variables:

$$w_{i,t} = prob(s_{i,t} = 1 \mid \Pi_{i,t}) = \frac{\exp(\theta_0 + \theta_1 \cdot |DA|_{i,t} + \theta_2 \cdot DISP_{i,t} + \theta_3 \cdot CRISIS_t)}{1 + \exp(\theta_0 + \theta_1 \cdot |DA|_{i,t} + \theta_2 \cdot DISP_{i,t} + \theta_3 \cdot CRISIS_t)},$$

$$1 - w_{it} = prob(s_{it} = 2 \mid \Pi_{it}) = 1 - prob(s_{it} = 1 \mid \Pi_{it}), \tag{6}$$

where Π_{it} is a 3 x 1 vector of variables for controlling the state probabilities. The three variables include the absolute value of discretionary accruals ($|DA|$) to gauge the degree of earnings management, the analysts' forecast dispersion (*DISP*) to measure the level of information asymmetry (or uncertainty), and the market crisis dummy (*CRISIS*). In the next section, we will detail the measurement of these variables. We label the specification as Model 5.

4. Sample and measure of variables

4.1 Sample

We obtained financial statement data (i.e., accounting data) from Compustat. The market data, i.e., stock return and trading volume, are collected by the Centre for Research in Security Prices (CRSP) database. Analyst forecast data are obtained from the Institutional Brokers Estimate Service (I/B/ES) database. Firms in the financial industries (SIC code 6000-6999) are excluded from the study and 5,678 non-financial U.S. firms with all the required data from 1996 to 2015 are included. As a result, we have 31,469 firm-year observations for the statistical analyses.

Our empirical analyses are based on a regression of stock returns on a set of explanatory variables derived from fundamental analysis and technical analysis. Since our focus is to predict stock returns, the dependent variable in our regression is subsequent quarterly returns, i.e., stock returns following the quarter in which these explanatory variables are measured at that year. Moreover, in this study, we introduce several information variables to determine the weighting given to each type of analysis. Below we detail the measurement of these variables.

4.2 Measure of earnings management

Earnings management is not always observable by market participants. Therefore, we use discretionary accruals as a proxy for this variable (e.g., Bergstresser and Philippon, 2006; Cheng and Warfield, 2005; Chi and Gupta, 2009; Datta et al., 2013; Larcker et al., 2007). Because managers can manipulate the reported earnings upward or downward, we adopt the absolute (unsigned) value of discretionary accruals to gauge the degree of earnings management. To ensure the robustness of our empirical results, we also analyze the effects of earnings management on earnings predictability using the signed values of discretionary accruals.

To estimate the number of discretionary accruals, we employ a cross-sectional version of the modified Jones (1991) model by controlling for firm performance. We adopt this revised measure because Kothari et al. (2005) report that performance-matched discretionary accruals enhance the reliability of the inferences made in earnings management research.[1] To estimate the number of discretionary accruals by year–industry based on two-digit SIC codes, we use the following equation:

$$\frac{TACC_{i,t}}{TA_{i,t-1}} = \alpha_0 \frac{1}{TA_{i,t-1}} + \alpha_1 \frac{\Delta SALE_{i,t} - \Delta AR_{i,t}}{TA_{i,t-1}} + \alpha_2 \frac{PPE_{i,t}}{TA_{i,t-1}} + \alpha_3 ROA_{i,t-1} + \varepsilon_{i,t}. \tag{7}$$

In Equation (7), *TACC* equals total accruals and *TA* is the number of total assets; Δ*SALES* equals the change in net sales and Δ*AR* represents the change in net accounts receivable; *PPE* is the amount of net property, plant, and equipment; and *ROA* equals the rate of return on assets. Finally, ε represents an error term. Subscripts *i* and *t* denote the firm and year, respectively. The discretionary accruals (*DA*) are the residuals obtained from Equation (7).

4.3 Measures of information asymmetry (or uncertainty)

Following the literature (e.g., Affleck-Graves et al., 2002; Butler and Lang, 1991; Barron et al., 2009; Behn et al., 2008; Payne and Thomas, 2003), we use the dispersion of analysts' forecasts (*DISP*) to measure information asymmetry (or uncertainty). To calculate the *DISP*, we apply the following equation:

$$\begin{aligned} &Dispersion\ of\ Analysts'Forecast\ (DISP) \\ &\qquad = \frac{Standard\ Deviation\ of\ Analysts'\ Earnings\ Forecasts}{|\ Mean\ Analysts'\ Earnings\ Forecast|}. \end{aligned} \tag{8}$$

Because the standard deviation of the analysts' forecasts increases with their average, we normalize the standard deviation of analysts' earnings forecasts by the absolute value of the

[1] Since prior studies on earnings management estimate discretionary accruals using the original Jones model (without controlling for firm performance), we replicate all the regressions using this alternative measure. The results (not tabulated) are similar to the main results.

average earnings forecast. To compute *DISP*, we follow the literature and remove observations of firms with a zero average earnings forecast because it results in a zero in the denominator of Equation (8) (e.g., Diether et al., 2002; Payne and Thomas, 2003).

4.4 Proxy of market crisis

To capture the effect of the market crisis on the choice between fundamental analysis and technical analysis, we define a dummy variable for the market crisis (*CRISIS*) using the negative value of the U.S. annual GDP growth rate (i.e., 2008 and 2009).

5. Empirical results

5.1 Descriptive statistics

Table 1 presents the descriptive statistics of the explained and explanatory. The mean (median) of *RET* is 0.005 (0.019). The mean (median) of explanatory variables *PRET*, *PVOL*, *CF/P*, *E/P*, and *B/M* equal 0.019 (0.058), 18.046 (18.042), 0.012 (-0.003), 0.064 (0.074), 0.491 (0.423), respectively. As for the information variables for the weighting given to each type of analysis, the mean (median) of |*DA*| equals 0.156 (0.063); the mean (median) of *DISP* equals 0.154 (0.049). Table 2 reports the Pearson correlation coefficients of all the variables. As shown, multicollinearity is not a serious issue in our analysis.

5.2 Estimation results of highbred models

Table 3 lists the estimation results of the two models involving just one type of information. Panel A shows the results of the technical analysis (Model 1), while those of the fundamental analysis (Model 2) are presented in Panel B. With the 1% significance level as a criterion, the estimates of the effects of the market variables and the accounting ratios are significant. In specific, the coefficient on *PRET* is 0.026 (p-value < 0.001), which implies a positive autocorrelation pattern in stock returns. The coefficient on *PVOL* equals 0.023 (p-value < 0.001), which shows a positive relation between stock returns and trading volume. Next, as shown in Panel B, *CF/P* is significantly negative (coeff. = -0.075 and p-value < 0.001), which is consistent with the notion that liquid assets earn a lower return. E/P and B/P are significant and positive, which implies that earnings-to-price ratios and book-to-market ratios are positively related to future returns.

5.3 Estimation results of hybrid models

Table 4 presents the estimation results of the hybrid model using the conventional regression method (Model 3). First, all the market variables and the accounting ratios are significant and the signs of the estimated coefficients are consistent with Table 3. Next, we use the regime-switching system to develop the hybrid models and test our four hypotheses. Table 5 shows the results of the hybrid stock return prediction model with static weights (Model 4). Consistent with Table 4, the estimates of the market variable and accounting ratios are significant and their signs are unchanged. However, the results of Model 4 further indicate that the estimate of σ_1 (0.132) is significantly lower than σ_2 (0.282). This result reveals that the high and low volatility state corresponds to the forecasting technique of the fundamental analysis and technical analysis, respectively. This finding suggests that market investors give more weight to fundamental analysis for stocks with more volatile prices, which supports our H1.

Last but not least, Table 6 presents the estimation results of Model 5. Compared with Model 4, Model 5 further examines the effect of the three determinant variables on the non-uniform weightings addressed in this study. First, the coefficients on |*DA*| and *DISP* are significant and negative (coeff. = -0.427 and p-value < 0.001; coeff. = -5.219 and p-value <

0.001). Second, the coefficient on *CRSIS* is significantly positive (coeff. = 2.094 and p-value < 0.001). These results support our H2, H3, and H4.

5.4 Implications and discussion

The key issue in this study is to examine the non-uniform weightings given to each forecasting technique. We assume a state-varying system in which an unobservable state variable with possible outcomes of one and two is designed, and the two states are linked with the fundamental analysis and technical analysis. Moreover, the probability of state is conditional on several determinant variables: discretionary accruals, analysts' forecast dispersion, and crisis occurrence. Moreover, we consider not only the dynamics of return means but also the dynamics of return volatility. Specifically, in our hybrid models, two measures for the standard errors are designated for capturing the dynamics of return volatility to examine whether market participants give more or less weight to fundamental analysis versus technical analysis for stocks with volatile prices.

As shown in Table 5, the *average* weights on technical analysis and fundamental analysis are 60.72% and 39.28%, respectively. While the former is larger than the latter, its 95% confidence interval does not overlap with the values of zero and one. This finding supports the notion that both market and accounting data are employed by stock investors. Table 6 further provides evidence of the pattern of dynamic weights. First, the negative coefficient of |*DA*| implies that the weight given to technical analysis is decreased and the weight given to fundamental analysis is increased accordingly for firms associated with high discretionary accounting choices. This result is consistent with the notion that the discretionary accounting choices of firms include incremental information content (i.e., the perspective of efficient earnings management) and investors, therefore, pay more attention to accounting-based information. This result supports our second hypothesis (H2). The negative coefficient of *DISP* indicates that for firms with a high degree of information asymmetry or uncertainty, one should give less weighting to technical analysis and thus give greater weighting to accounting-based information. This result is consistent with our hypothesis three (H3): investors are more concerned with the intrinsic (or fair) values of securities by fundamental analysis when encountering information asymmetry or uncertainty.

Last but not least, the coefficient of the crisis dummy (i.e., *CRISIS*) is significant and positive. This result supports our fourth hypothesis (H4): for the stock market is experiencing a financial crisis, the weight given to technical analysis should be increased and accordingly, the weight given to fundamental analysis is decreased. However, our empirical findings reveal that the high and low volatility state corresponds to the forecasting technique of the fundamental analysis and technical analysis, respectively (i.e., $\sigma_2 > \sigma_1$, as shown in Tables 5 and 6). This finding implies that investors give greater weight to fundamental analysis for stocks with volatile prices. The result supports our first hypothesis (H1).

The difference between our H1 and H4 requires further explanation. First, as shown in Table 6, the estimates of σ_2 and σ_1 are 0.269 (26.9%) and 0.121 (12.1%), respectively. Therefore, we denote state two and one as the high and low volatility regime, respectively. The crisis dummy variable in this study is to identify the 2008-2009 financial crisis period. In this period, the S&P 500 lost about 56% of its value from the October 2007 peak and the VIX Index more than tripled (i.e., 300%). This study proposes that the crisis period was associated with irrational behaviors, such as overreaction and herding. We hypothesize that fundamental analysis was invalid during these extremely volatile periods and thus stock investors gave lesser weight to fundamental analysis. Unlike the crisis period, the high volatility regime (or state two) in our

Models 4 and 5 could be defined as an unusual condition, rather than a crisis situation. Moreover, we argue that the increased/decreased deviation from intrinsic values based on the fundamental analysis approach closely associates with the high/low volatility in stock returns. From the standpoint of nonlinear adjustment, the speed of convergence toward intrinsic values derived from fundamental analysis would be expected to increase as the deviation from intrinsic values rises in absolute value. This explains why the fundamental analysis method corresponds with the state of high volatility, as reflected in our H1.

5.5 Model fitness performance

This study develops five different empirical models for predicting stock returns. The next question is whether the hybrid model with non-uniform weightings on each type of analysis (i.e., Model 5) is a more effective model in matching dynamics of stock returns when compared to the other models (i.e., Models 1 to 4). Table 7 reports the value of the log-likelihood function, the Akaike information criterion (AIC), and the Schwarz value, three common model selection statistics. Importantly, Model 5 (the hybrid model with non-monotonic weights) has the highest value of the log-likelihood function, AIC, and Schwarz value in comparison with Models 1 to 4.

Next, we discuss the model forecast performance in term of MSE (Mean Square Error) and MAE (Mean Absolute Error). Notably, a two-state system is defined in Models 4 and 5. Regime I (namely, $s_{i,t}$ = 1) is set when subsequent stock return (i.e., $RET_{i,t+1q}$) depends on technical analysis approach with volatility σ_1, while regime II (namely, $s_{i,t}$ = 2) is set when we use fundamental analysis approach with volatility σ_2 to fit subsequent stock return. While the state variable of $s_{i,t}$ in the models is unobservable, one could use the observed data to estimate the specific regime probability for each stock at each time point. Therefore, stock return and return volatility for each stock at any point of time can be determined as the weighted average of stock return and return volatility at various states, weighted according to their respective probabilities.

Panel A of Table 8 lists MSE and MAE for stock return. The difference among various competing models is marginal (e.g., MAE for Model 1 = 0.045 and MAE for Model 5 = 0.044). Panel B of Table 8 shows MSE and MAE for return volatility. Our result indicates that Model 5 associates with the minimum forecast error for return volatility (e.g., MAE for Model 1 = 0.179 and MAE for Model 5 = 0.161). Our conclusion is clear: Model 5, in which both market and accounting variables are incorporated via a regime-switching approach, is associated with better performance in fitting the variation of stock returns. However, fitting return volatility, rather than stock return, is to be thanked for the benefits stemming from such improved effectiveness.

5.6 Dynamic versus statistic weights

A comparison of Equations (5) and (6) reveals the difference between Model 4 and Model 5, distinguished by static versus varying weights. Specifically, Equation (5) for the hybrid model with static weights uses constant weightings, w and $(1 - w)$, to evaluate the impact of each forecasting technique. As shown in Table 5, the weights given to technical and fundamental analysis approach are 60.72% and 39.28%, respectively, when Model 4 is employed. Model 5 uses Equation (6) to develop endogenous and non-uniform weightings, w_{it} and $(1 - w_{it})$. Moreover, Model 4 could be considered a special case of Model 5 with the restrictions $\theta_1 = \theta_2 = \theta_3 = 0$. Importantly, the probabilities of the specific state, namely, $prob(s_{it} = 1 \text{ or } 2|\Pi_{it})$, are estimated by the data themselves and will change across stocks and over time. We estimate the model parameters and the probabilities using the maximum likelihood estimation method, detailed in the Appendix.

Using the year of 2009 as an illustrative example, Panels A and B of Figure 1 depict the estimated probabilities of regimes I and II, respectively, which represent the weights for the technical and fundamental analysis approach when Model 5 is adopted. First, comparing Panels A and B, the estimated weights for each approach flexibly range from zero to one across firm-quarter observations. This finding is consistent with the argument of non-monotonic weights given to each type of analysis change across stocks. Next, we use the year of 2015 as another example and graph the estimated probabilities of regimes I and II in Figure 2. Comparing Figures 1 and 2, the weight given to the technical analysis approach in 2009 is higher than that in 2015. This finding supports the argument of weights given to each type of analysis varying over time.

Last but not least, the average values of the estimated probabilities of regime I (technical analysis approach) and regime II (fundamental analysis approach) over the whole period from 1996 to 2015 are 51.15% and 48.85%, respectively. While the former is higher than the latter, its 95% confidence interval does not overlap with the values of zero and one. This finding supports the notion that both information involved in technical and fundamental analysis approach should be employed when predicting stock returns.

5.7 Explanatory variables for stock return or determinant variables of optimal weights?

In this study, we propose the three variables to control the optimal weights given to accounting and market information and then develop a hybrid model with dynamic weights (i.e., Model 5). An alternative model specification is to include all the variables as the explanatory variables for stock return prediction. Therefore, we rerun Model 3 and add all three of the determinant variables of optimal weights as the explanatory variables in the conventional regression. The estimation results are listed in Table 9. Compared with Table 6, Model 5 (the hybrid model with non-monotonic weights) still has a higher value of the log-likelihood function, AIC, and Schwarz value.

5.8 Robustness tests

We conduct various tests to check the robustness of the primary results discussed above. These tests are to use alternative measures of subsequent stock return, discretionary accruals and information asymmetry (or uncertainty).

In the empirical analysis discussed above, we use the subsequent quarterly stock return (i.e., $RET_{i,t+1q}$) as the dependent variable. We obtain similar results (not shown) when using the subsequent monthly stock returns (e.g., $RET_{i,t+1m}$). We use discretionary accruals adjusted for lagged performance, following the argument by Kothari et al. (2005) that performance-matched discretionary accrual measures enhance the reliability of the inferences from earnings management research. Since some prior studies on earnings management estimate discretionary accruals using the Jones model without controlling for firm performance, we replicate the empirical tests using this alternative measure of discretionary accruals. The results (not tabulated) are similar to those reported in the tables. We use analysts' forecast dispersion as the proxy of information asymmetry or uncertainty (e.g., Krishnaswami and Subramaniam, 1999; Maskaraa and Mullineaux, 2011; Richardson, 2000; Thomas, 2002). Prior studies also employ idiosyncratic risk to measure the level of a firm's information asymmetry (e.g., Barry and Brown, 1985; Dierkens, 1991; Moeller et al., 2007). We follow Ang et al. (2009) and Fu (2009) to run the daily Fama–French (1993) three-factor model and use the standard deviation of the regression residuals as the measure of idiosyncratic risk. We obtain similar results (not shown) when using idiosyncratic risk to replace analysts' forecast dispersion.

In summary, we use alternative measures of the variables to conduct various robustness tests and find our conclusions to be largely consistent with those based on the models and measures of variables in the primary analyses. The dynamic patterns involved in the weightings for each type of analysis appear to be robust.

6. Conclusions and future research directions

This study is one of the first to employ a regime-switching technique to develop a hybrid model with endogenous and non-monotonic weightings on fundamental analysis and technical analysis. Examining 31,469 non-financial firm–year observations in the United States from 1996 to 2015, we show that stock investors consider both accounting ratios in fundamental analysis and market variables in technical analysis. However, the weightings given to each type of analysis change across stocks and over time. In particular, the weight given to fundamental analysis is positively related to return volatility, accounting accruals, and analysts' forecast dispersion, but negatively related to the market crisis dummy. The opposite is true for the weighting given to technical analysis.

The implications of our empirical results are consistent with the following. First, for the firms with incremental information enhanced by accounting discretionary accruals, investors put more emphasis on fundamental analysis and thus reduce the emphasis on technical analysis. Investors are more concerned with intrinsic value based on fundamental analysis when encountering a high degree of information asymmetry or uncertainty, and thus increase and decrease the weighting given to fundamental analysis and technical analysis, respectively. Third, for stocks with volatile prices, stock returns are more influenced by accounting ratios in fundamental analysis. Conversely, market participants give more weighting to market variables in technical analysis for stocks with stabilized prices. However, when the market is crashing, the weight given to technical analysis should be increased and the weight given to fundamental analysis should be decreased.

Several limitations of this study should be mentioned. First, our results are limited by the chosen variables. In particular, we use the three accounting-based ratios suggested by Patricia et al. (2001). Other accounting ratios can also be used to explain stock returns (see Lev and Thiagarajan, 1993; Ou and Penman, 1989), but the aim of this study is not to find alternative accounting ratio-based variables for stock return prediction. For reasons of expediency, this study only uses the three common accounting ratios to establish the fundamental analysis. Next, we use past stock return and trading volume to develop the technical analysis. Different technical analysis skills have been proposed and implemented in the literature. This study considers several variables to control the regime-switching process to examine the non-uniform weightings given to each type of analysis. Future studies might explore other testing variables (e.g., liquidity addressed by Avramov et al., 2016 and investor sentiment by Stambaugh et al., 2012). Finally, the empirical results in this study are an ex-post analysis to explain the factors that affect stock returns. We ever attempted using the results by Model 5 to build up a trading strategy to make abnormal returns exceeding other models. However, the difference is insignificant. It implies that the ex-ante forecasting stock market return is a challenging task (e.g., Zielonka, 2004; Teixeira and Oliveira, 2010).

Appendix:

Maximum likelihood estimation

To estimate the model, we want to find the set of parameters that maximize the likelihood function. As shown in Equation (4), the two-state system is defined as:

$$RET_{i,t+1q} = \begin{cases} const_1 + \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t} + u_{i,t}, \quad u_{i,t} \sim N(0,\sigma_1) \quad if \quad s_{i,t} = 1 \\ const_2 + \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t} + u_{i,t} \quad , \\ \quad u_{i,t} \sim N(0,\sigma_2) \quad if \quad s_{i,t} = 2, \end{cases}$$

Given the Gaussian specification for the error term, the corresponding *PDF* (probability density function) for each state is:

$$\begin{cases} PDF(s_{i,t}=1) = \dfrac{1}{\sqrt{2\Pi}\sigma_1} \exp\{\dfrac{-[RET_{i,t+1q} - (const_1 + \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t})]^2}{2 \times \sigma_1^2}\}, \\ PDF(s_{i,t}=2) = \dfrac{1}{\sqrt{2\Pi}\sigma_2} \exp\{\dfrac{-[RET_{i,t+1q} - (const_2 + \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t})]^2}{2 \times \sigma_2^2}\}. \end{cases}$$

In this study, the probabilities of state are conditional on three information variables:

$$w_{i,t} = prob(s_{i,t} = 1 | \Pi_{i,t}) = \frac{\exp(\theta_0 + \theta_1 \cdot |DA|_{i,t} + \theta_2 \cdot DISP_{i,t} + \theta_3 \cdot CRISIS_t)}{1 + \exp(\theta_0 + \theta_1 \cdot |DA|_{i,t} + \theta_2 \cdot DISP_{i,t} + \theta_3 \cdot CRISIS_t)},$$

$$1 - w_{it} = prob(s_{it} = 2 | \Pi_{it}) = 1 - prob(s_{it} = 1 | \Pi_{it}).$$

We then multiply the *PDF* for each state by the corresponding probability of state to yield the weighted *PDF* as the likelihood function for firm *i* at time *t*:

$$l_{i,t} = prob(s_{i,t} = 1 | \Pi_{i,t}) \times PDF(s_{i,t} = 1) + prob(s_{i,t} = 2 | \Pi_{i,t}) \times PDF(s_{i,t} = 2).$$

Finally, we create a log-likelihood function Ψ that is the sum of the natural logarithm of the likelihood function for all firms and times:

$$\Psi = \sum_{i=1}^{N}\sum_{t=1}^{T} \ln l_{it}(PRET_{it}, PVOL_{it}, (CF/P)_{it}, (E/P)_{it}, (B/M)_{it}, |DA|_{it}, DISP_{it}, CRISIS_{i,t}; \Omega),$$

where Ω is a vector of population parameters containing the unknown elements $cosnt_1$, β_1, β_2, σ_1, $cosnt_2$, γ_1, γ_2, σ_2, θ_0, θ_1, θ_2, and θ_3. Finally, we use OPTIMUM, a software package from GAUSS, and the built-in Broyden–Fletcher–Goldfarb–Shanno algebra to search for the Ω that maximizes the above log-likelihood function.[2]

[2] The structural and statistical properties of the OPTIMUM function are well documented in the GAUSS handbook. This study thus omits the statistical properties of the model estimation.

References

Affleck-Graves, J., Callahan, C.M. and Chipalkatti, N. (2002) Earnings predictability, information asymmetry and market liquidity, *Journal of Accounting Research* 40, 561-583.

Akaike, H. (1976) Canonical correlation analysis of time series and use of an information criterion, In R. K. Mehra and D. G. Lainioties (Eds.), *System identification: Advance and case studies*, New York: Academic Press, 27-96.

Ang, A., Hodrick, R.J., Xing, Y. and Zhang X. (2009) High idiosyncratic volatility and low returns: international and further US evidence, *Journal of Financial Economics* 91, 1-23.

Avramov, D., Cheng, S. and Hameed, A. (2016) Time-varying liquidity and momentum profits, *Journal of Financial and Quantitative Analysis* 51, 1897-1923.

Avramov, D., Kaplanski G. and Levy, H. (2018) Talking Numbers: Technical versus fundamental investment recommendations, *Journal of Banking and Finance* 92, 100-114.

Balsam, S., Bartov, E., and Marquardt, C. (2002) Accruals management, investor sophistication and equity valuation: Evidence from 10-Q filings, *Journal of Accounting Research* 40, 987-1012.

Barron, O.E., Stanford, M.H. and Yu, Y. (2009) Further Evidence on the relation between analysts' forecast dispersion and stock returns, *Contemporary Accounting Research* 26, 329-357.

Barry, C. and Brown, S. (1985) Differential information and security market equilibrium, *Journal of Financial and Quantitative Analysis* 20, 407-422.

Basu, S. (1983) The relationship between earnings yield, market value, and return for NYSE common stocks: further evidence, *Journal of Financial Economics* 12, 129-156.

Behn, B.K., Choi, J.H. and Kang, T. (2008) Audit quality and properties of analyst earnings forecasts, *The Accounting Review* 83, 327-349.

Bergstresser, D., and Philippon, T. (2006). CEO incentives and earnings management. *Journal of Financial Economics* 80, 511-529.

Bisoi, R. and Dash, P. (2014) A hybrid evolutionary dynamic neural network for stockmarket trend analysis and prediction using unscented Kalman filter, *Applied Soft Computing* 19, 41-56.

Brock, W., Lakonishok, J. and LeBaron, B. (1992) Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance* 47, 1731-1764.

Butler, K.C. and Lang, L.H. (1991) The forecast accuracy of individual analysts: Evidence of systematic optimism and pessimism, *Journal of Accounting Research* 29, 150-156.

Burgstahler, D.C., and Dichev, I.D. (1997) Earnings management to avoid earnings decreases and losses, *Journal of Accounting and Economics* 24, 99-126.

Burgstahler D., and Eames, M. (2006) Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises, *Journal of Business Finance and Accounting* 33, 633-652.

Chan, L.K., Jegadeesh, C.N. and Lakonishok, J. (1995) Evaluating the performance of value versus glamour stocks: The impact of selection bias, *Journal of Financial Economics* 38, 269-296.

Cheng, Q. and Warfield, T.D. (2005) Equity incentives and earnings management. *The Accounting Review* 80, 441-476.

Chavarnakul, T. and Enke, D. (2009) A hybrid stock trading system for intelligent technical analysis-based equivolume charting, *Neurocomputing* 72, 3517-3528.

Datta, S., Iskandar-Datta, M. and Singh, V. (2013) Product market power, industry structure, and corporate earnings management, *Journal of Banking and Finance* 37, 3273-3285.

Davis, J.L. (1994) The cross-section of realized stock returns: The pre-COMPUSTAT evidence, *Journal of Finance* 49, 1579-1594.

Dechowa, P.M., Hutton, A.P., Meulbroekb, L. and Sloana, R.G. (2001) Short-sellers, fundamental analysis, and stock returns, *Journal of Financial Economics* 61, 77-106.

Dechow, P.M., Ge, W. and Skinner, D.J. (2010) Understand earnings quality: A review of proxies, their determinants and their consequences, *Journal of Accounting and Economics* 50, 344-401.

Dechow, P.M., Hutton, A.P. and Sloan, R.G. (1999) An empirical assessment of the residual income valuation model, *Journal of Accounting and Economics* 34, 1-34.

Dechow, P.M., and Skinner, D.J. (2000) Earnings management: Reconciling the views of accounting academics, practitioners and regulators, *Accounting Horizons* 14, 235-250.

Dierkens, N. (1991) Information asymmetry and equity issues, *Journal of Financial and Quantitative Analysis* 26, 181-199.

Diether, K.B., Malloy, C.J. and Scherbina, A. (2002) Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113-2141.

Fama, E.F. and French, K.R. (1992) The cross-section of expected stock returns, *Journal of Finance* 47, 427-466.

Fama, E.F. and French, K.R. (1993) Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-57.

Frankel, R. and Lee, C.M.C. (1998) Accounting valuation, market expectations, and cross-sectional stock returns, *Journal of Accounting and Economics* 25, 283-319.

Fu, F. (2009) Idiosyncratic risk and the cross-section of expected stock returns, *Journal of Financial Economics* 91, 24-37.

Garfinkel, J.A. (2009) Measuring investors' opinion divergence, *Journal of Accounting Research* 47, 1317-1348.

Garfinkel, J.A. and J. Sokobin (2006) Volume, opinion divergence, and returns: A study of post-earnings announcement drift, *Journal of Accounting Research* 44, 85-112.

Graham, J.R., Harvey, C.R., and Rajgopal, S. (2005) The economic implications of corporate financial reporting, *Journal of Accounting and Economics* 40, 3-73.

Hann, R., Lu, Y., and Subramanyam, K.R. (2007) Uniformity versus flexibility: evidence from pricing of the pension obligation, *The Accounting Review* 82,107-137.

Healy, P.M., and Palepu, K.G. (1993) The effect of firms' financial disclosure strategies on stock prices, *Accounting Horizons* 7, 1-11.

Hoque, H.A.A.B., Kim, J.H. and Pyun, C.S. (2007) A comparison of variance ratio tests of random walk: a case of Asian emerging stock markets, *International Review of Economics and Finance* 16, 488-502.

Jaffe, J., Keim, D.B. and Westerfield, R. (1989) Earnings yields, market values, and stocks returns, *Journal of Finance* 44, 135-148.

Johnson, T. (2004) Forecast dispersion and the cross section of expected returns, *Journal of Finance* 59, 1957-1978.

Jones, J.J. (1991) Earnings management during import relief investigations, *Journal of Accounting Research* 29, 193-228.

Kazem, A., Sharifi, E., Hussain, F.K., Saberi, M., and Hussain, O.K. (2013) Support vector regression with chaos-based firefly algorithm for stock market price forecasting, *Applied Soft Computing*, 13, 947-958.

Kim, J.H. and Shamsuddin, A. (2008) Are Asian stock markets efficient? Evidence from new multiple variance ratio tests, *Journal of Empirical Finance* 15, 518-532.

Kothari, S.P., Leone, A.J. and Wasley, C.E. (2005) Performance matched discretionary accrual measures, *Journal of Accounting and Economics* 39, 163-197.

Krishnan, G. (2003) Audit quality and the pricing of discretionary accrual, *Auditing* 22, 109-126.

Lakonishok, J., Shleifer, A. and Vishny, R. (1994) Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541-1578.

Larcker, D.F., Richardson, S.A. and Tuna, I. (2007) Corporate governance, accounting outcomes, and organizational performance, *The Accounting Review* 82, 963-1008.

Lee, C. M. and Swaminathan, B. (2000) Price momentum and trading volume, *Journal of Finance* 55, 2017-2069.

Lim, K.P., Brooks, R.D. and Kim, J.H. (2008) Financial crisis and stock market efficiency: empirical evidence from Asian countries, *International Review of Financial Analysis* 17, 571-591.

Llorente, G., Michaely, R., Saar, G. and Wang, J. (2002) Dynamic volume-return relation of individual stocks, *Review of Financial Studies* 15, 1005-1047.

Lo, A.W., Mamaysky, H. and Wang, J. (2000) Foundations of technical analysis: Com-putational algorithms, statistical inference, and empirical implementation, *Journal of Finance* 55, 1705-1770.

Manda, K. (2010) Stock market volatility during the 2008 financial crisis, Working paper (Stern School of Business, New York University).

Menkhoff, L. (2010) The use of technical analysis by fund managers: International evidence, *Journal of Banking and Finance* 34, 2573-2586.

Menkhoff, L. and Taylor, M.P. (2007) The obstinate passion of foreign exchange pro-fessionals: Technical analysis, *Journal of Economic Literature* 45, 936-972.

Metghalchi, M., Chang, Y. H. and Marcucci, J. (2008) Is the Swedish stock market efficient? Evidence from some simple trading rules, *International Review of Financial Analysis* 17, 475-490.

Mitra, S.K. (2011) How rewarding is technical analysis in the Indian stock market? *Quantitative Finance*, 11, 287-297.

Moeller, S.B., Schlingemann, F.P. and Stulz, R.M. (2007) How do diversity of opinion and information asymmetry affect acquirer returns? *Review of Financial Studies* 20, 2047-2078.

Myers, J.N., Myers, L.A., and Skinner, D. J. (2007) Earnings momentum and earnings management, *Journal of Accounting, Auditing, and Finance* 22, 249-284.

Nazárioa, R., Silva, J.L., Sobreiro, V.A. and Kimuraa, H. (2017) A literature review of technical analysis on stock markets, *Quarterly Review of Economics and Finance* 66, 115-126.

Ohlson, J. (1995) Earnings, book values, and dividends in security valuation, *Contemporary Accounting Research* 11, 661-687.

Oppenheimer, H. R. and Schlarbaum, G. G. (1981) Investing with Ben Graham: An Ex Ante test of the efficient markets hypothesis, *Journal of Financial and Quantitative Analysis* 16, 341-360.

Park, C.H., and Irwin, S.H. (2007) What do we know about the profitability of technicalanalysis? *Journal of Economic Surveys* 21, 786-826.

Payne, J. and Thomas, W. (2003) The implications of using stock-split adjusted I/B/E/S data in empirical research, *The Accounting Review* 78, 1049-1067.

Rosenberg, B., Reid, K. and Lanstein, R. (1985) Persuasive evidence of market inefficiency. *Journal of Portfolio Management* 11, 9-17.

Sankar, M., and Subramanyam, K.R. (2001) Reporting discretion and private information communication through earnings, *Journal of Accounting Research* 39, 365-386.

Schwarz, G. (1978) Estimating the dimension of a model, *Annual of Statistics* 6, 461-464.

Sloan, R.G. (1996) Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71, 289-315.

Scott, R.W. (2000) Financial Accounting Theory, 2nd Ed. New Jersey: Prentice Hall.

Stambaugh, R.F. Yu, J. and Yuan, Y. (2012) The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.

Stattman, D. (1980) Book values and stock returns, *The Chicago MBA: A Journal of Selected Papers* 4, 25-45.

Teixeira, L.A. and Oliveira, A.L.I.D. (2010) A method for automatic stock trading combining technical analysis and nearest neighbor classification, *Expert Systems with Applications* 37, 6885-6890.

Ticknor, J.L. (2013) A Bayesian regularized artificial neural network for stock market forecasting, *Expert Systems with Applications* 40, 5501-5506.

Tucker, J.W., and Zarowin, P. (2006) Does income smoothing improve earnings informativeness? *The Accounting Review* 81, 251-270.

Vanstone, B. and Finnie, G. (2009) An empirical methodology for developing stock-market trading systems using artificial neural networks, *Expert Systems with Applications* 36, 6668-6680.

Wei, L.Y., Chen, T.L., and Ho, T.H. (2011) A hybrid model based on adaptive-network-based fuzzy inference system to forecast Taiwan stock market, *Expert Systems with Applications* 38, 13625-13631.

Yamamoto, R. (2012). Intraday technical analysis of individual stocks on the Tokyo stock exchange, *Journal of Banking and Finance* 36, 3033-3047.

Zhu, H., Jiang, Z.Q., Li, S.P., and Zhou, W.X. (2015) Profitability of simple technical trading rules of Chinese stock exchange indexes, *Physica A: Statistical Mechanics and its Applications* 439, 75-84.

Zhu, Y., and Zhou, G. (2009) Technical analysis: An asset allocation perspective on the use of moving averages, *Journal of Financial Economics* 92, 519-544.

Zielonka, P. (2004) Technical analysis as the representation of typical cognitive biases, *International Review of Financial Analysis* 13, 217-225.

Table 1
Descriptive statistics of variables

Variable	Mean	Standard Dev.	Median	Q1	Q3
RET	0.005	0.211	0.019	-0.101	0.131
PRET	0.019	0.451	0.058	-0.216	0.292
PVOL	18.046	1.516	18.042	16.978	19.090
CF/P	0.012	0.135	-0.003	-0.044	0.034
E/P	0.064	0.113	0.074	0.031	0.116
B/M	0.491	0.347	0.423	0.256	0.646
|*DA*|	0.156	0.276	0.063	0.026	0.151
DISP	0.154	0.313	0.049	0.022	0.126
CRISIS	0.052	0.221	0.000	0.000	0.000

Variable definitions:

RET	=	Subsequent quarterly return
PRET	=	Past annual return
PVOL	=	Natural log of past annual trading volume
CF/P	=	Cash-flow-to-price ratio
E/P	=	Earnings-to-price ratio
B/M	=	Boot-to-market ratio
|*DA*|	=	Absolute value of discretionary accruals
DISP	=	Dispersion of analysts' forecasts
CRISIS	=	Market crisis dummy: one for 2008 and 2009; zero for others

The sample consists of 31,469 firm-year observations obtained with 5,678 unique firms for the period from 1996 to 2015.

Table 2
Correlation matrix of variables

	RET	*PRET*	*PVOL*	*CF/P*	*E/P*	*B/M*	*|DA|*	*DISP*	*CRISIS*
RET	1.000								
PRET	0.057	1.000							
PVOL	0.015	0.025	1.000						
CF/P	-0.054	-0.090	-0.069	1.000					
E/P	0.069	0.124	0.001	-0.125	1.000				
B/M	0.060	-0.314	-0.229	0.017	0.082	1.000			
|DA|	0.019	0.033	0.084	0.046	-0.124	-0.051	1.000		
DISP	0.015	-0.062	-0.053	0.036	-0.259	0.154	0.052	1.000	
CRISIS	0.058	0.156	0.085	-0.062	-0.020	0.039	0.113	0.041	1.000

The sample consists of 31,469 firm-year observations for the period from 1996 to 2015. The definition of the variables is consistent with Table 1.

Table 3
Estimation results of the highbred models

$$RET_{i,t+1q} = const. + \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t} + u_{i,t}, \qquad u_{i,t} \sim N(0,\sigma)$$
$$RET_{i,t+1q} = const. + \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t} + u_{i,t}, \qquad u_{i,t} \sim N(0,\sigma)$$

Panel A: Technical analysis approach (Model 1)

	Coefficient	S.D.	t-value	p-value
Const.	-0.029	0.017	-1.724	0.042
PRET	0.026	0.003	9.992	0.000
PVOL	0.002	0.001	2.000	0.023
σ	0.211	0.001	251.214	0.000
Log-likelihood	4306.921			

Panel B: Fundamental analysis approach (Model 2)

	Coefficient	S.D.	t-value	p-value
Const.	-0.018	0.002	-8.279	0.000
CF/P	-0.075	0.009	-8.629	0.000
E/P	0.109	0.011	10.180	0.000
B/P	0.034	0.003	9.936	0.000
σ	0.210	0.001	250.381	0.000
Log-likelihood	4411.137			

Panels A and B present the estimation results of the technical analysis and fundamental analysis approach, respectively (see Equations (1) and (2) for the details of the model specifications). See Table 1 for variable definitions and sample descriptions. σ is the standard deviation of the error term in the regression.

Table 4
Estimation results of the hybrid model using the conventional regression method (Model 3)

$$
\begin{aligned}
RET_{i,t+1q} = const. &+ \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t} \\
&+ \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t} \\
&+ u_{i,t}, \quad u_{i,t} \sim N(0,\sigma).
\end{aligned}
$$

	Coefficient	S.D.	t-value	p-value
Const.	-0.101	0.016	-6.526	0.000
Technical analysis approach				
PRET	0.034	0.003	12.249	0.000
PVOL	0.004	0.001	5.012	0.000
Fundamental analysis approach				
CF/P	-0.065	0.009	-7.222	0.000
E/P	0.088	0.011	8.310	0.000
B/M	0.053	0.004	13.947	0.000
Error term in the regression				
SIGMA (σ)	0.210	0.001	249.714	0.000
Log-likelihood	4495.981			

This table presents the estimation results of the hybrid model using the conventional regression (see Equation (3) for the details of the model specifications). See Table 1 for variable definitions and sample descriptions. σ is the standard deviation of the error term in the regression.

Table 5
Estimation results of the hybrid model with static weights using the regime-switching method (Model 4)

$$RET_{i,t+1q} = \begin{cases} const_1 + \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t} + u_{i,t}, \quad u_{i,t} \sim N(0,\sigma_1) \quad if \quad s_{i,t} = 1 \\ \\ const_2 + \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t} + u_{i,t} \quad , \\ \quad u_{i,t} \sim N(0,\sigma_2) \quad if \quad s_{i,t} = 2, \end{cases}$$

$$w = prob(s_{i,t} = 1) = \frac{\exp(\theta_0)}{1+\exp(\theta_0)}, \qquad prob(s_{i,t} = 2) = 1 - w$$

	Coefficient	S.D.	t-value	p-value
Technical analysis approach				
Const₁ → $Const_1$	-0.020	0.014	-1.416	0.078
PRET	0.034	0.004	8.182	0.000
PVOL	0.003	0.001	4.025	0.000
σ_1	0.132	0.002	58.035	0.000
Fundamental analysis approach				
$Const_2$	-0.100	0.007	-13.548	0.000
CF/P	-0.164	0.024	-6.951	0.000
E/P	0.159	0.027	5.872	0.000
B/M	0.097	0.009	10.867	0.000
σ_2	0.282	0.003	92.806	0.000
Transition probability				
Const. (θ_0)	0.436	0.065	6.678	0.000
Log-likelihood	5738.753			

Weight on technical analysis = 0.6072 (60.72%)
Weight on fundamental analysis = 0.3928 (39.28%)

This table presents the estimation results of the hybrid model with static weights using the regime-switching technique. See Equations 4 and 5 for the details of the model specifications. See Table1 for variable definitions and sample descriptions.

Table 6
Estimation results of the hybrid model with dynamic weights using the regime-switching method (Model 5)

$$RET_{i,t+1q} = \begin{cases} const_1 + \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t} + u_{i,t}, \quad u_{i,t} \sim N(0,\sigma_1) \quad if \quad s_{i,t} = 1 \\ const_2 + \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t} + u_{i,t} \quad , \\ \quad u_{i,t} \sim N(0,\sigma_2) \quad if \quad s_{i,t} = 2, \end{cases}$$

$$w_{i,t} = prob(s_{i,t} = 1 \mid \Pi_{i,t}) = \frac{\exp(\theta_0 + \theta_1 \cdot |DA|_{i,t} + \theta_2 \cdot DISP_{i,t} + \theta_3 \cdot CRISIS_t)}{1 + \exp(\theta_0 + \theta_1 \cdot |DA|_{i,t} + \theta_2 \cdot DISP_{i,t} + \theta_3 \cdot CRISIS_t)}$$

$$1 - w_{it} = prob(s_{it} = 2 \mid \Pi_{it}) = 1 - prob(s_{it} = 1 \mid \Pi_{it}),$$

	Coefficient	S.D.	t-value	p-value
Technical analysis approach				
$Const_1$	-0.037	0.016	-2.301	0.011
PRET	0.043	0.004	10.124	0.000
PVOL	0.004	0.001	4.512	0.000
σ_1	0.121	0.002	69.821	0.000
Fundamental analysis approach				
$Const_2$	-0.071	0.005	-15.262	0.000
CF/P	-0.103	0.017	-6.117	0.000
E/P	0.094	0.017	5.406	0.000
B/M	0.081	0.007	12.313	0.000
σ_2	0.269	0.002	113.532	0.000
Transition probability				
Const. (θ_0)	0.592	0.053	11.112	0.000
|*DA*| (θ_1)	-0.427	0.105	-4.080	0.000
DISP (θ_2)	-5.219	0.510	-10.242	0.000
CRISIS (θ_3)	2.094	0.182	11.494	0.000
Log-likelihood	6021.029			

This table presents the estimation results of the hybrid model with dynamic weights. See Equations 4 and 6 for the details of the model specifications. See Table1 for variable definitions and sample descriptions. *CRISIS* is a dummy variable defined by the U.S. GDP growth rate (1 if the annual GDP growth rate is negative and 0 otherwise).

Table 7
Model selection statistics

	# of parameters	# of sample	Log-likelihood	AIC	Schwarz value
Highbred Models					
Model 1	3	31,469	4306.921	4407.137	4390.423
Model 2	4	31,469	4411.137	4406.137	4385.245
Hybrid Models					
Model 3	7	31,469	4495.981	4488.981	4459.732
Model 4	10	31,469	5738.753	5728.753	5686.969
Model 5	13	31,469	**6021.029**	**6008.029**	**5953.710**

This table summarizes the model selection statistics proposed by Akaike (1976) and Schwarz (1978).
The statistics AIC = Log-likelihood function value – No. No. is the number of model parameters.
The statistics Schwarz value = Log-likelihood function value - (No./2) x ln(#). # is the number of sample.
The value in **bold** style denotes the maximum value in the column.

Table 8
Forecasting performance of various models

Panel A: Forecast errors of stock return

	MSE (Mean Square Error)	MAE (Mean Absolute Error)
Highbred Models		
Model 1	0.156	0.045
Model 2	0.156	0.044
Hybrid Models		
Model 3	0.156	0.044
Model 4	0.156	0.044
Model 5	0.156	0.044

Panel B: Forecast errors of return volatility

	MSE (Mean Square Error)	MAE (Mean Absolute Error)
Highbred Models		
Model 1	0.034	0.179
Model 2	0.034	0.178
Hybrid Models		
Model 3	0.034	0.178
Model 4	0.029	0.162
Model 5	0.028#	0.161#

Two forecasting performance criteria, MSE and MAE, are applied to the evaluation of relative model performance in matching the pattern of stock return and return volatility. # denotes denotes the minimum value in the column.

Forecast errors of stock return:

MSE (Mean Square Error) = $$(N\times T)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(RET_{i,t}-RET_{i,t}^{e})^2$$

MAE (Mean Absolute Error) = $$(N\times T)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}|RET_{i,t}-RET_{i,t}^{e}|$$

Forecast errors of return volatility:

MSE (Mean Square Error) = $$(N\times T)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(u_{i,t}^2-\sigma_{i,t}^2)^2$$

MAE (Mean Absolute Error) = $$(N\times T)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}|u_{i,t}^2-\sigma_{i,t}^2|$$

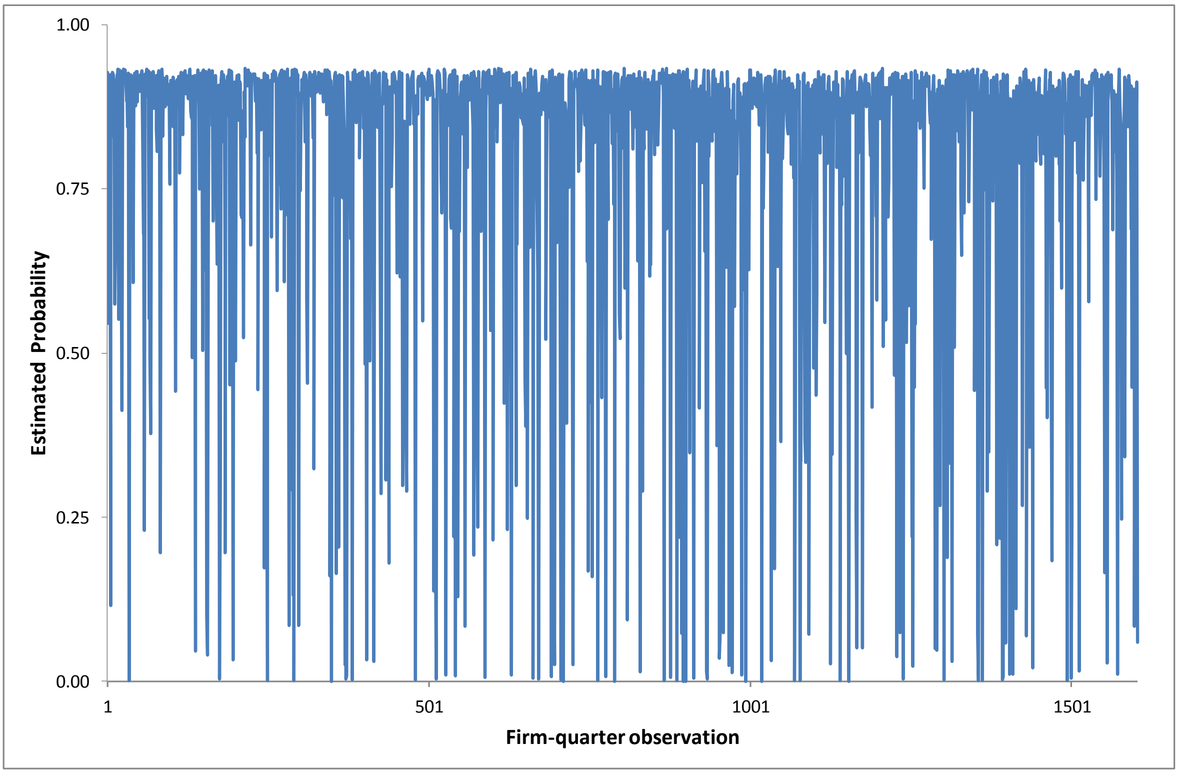
Table 9
Estimation results of the model using all the variables as the explanatory variables for stock return

$$
\begin{aligned}
RET_{i,t+1q} = const. &+ \beta_1 \times PRET_{i,t} + \beta_2 \times PVOL_{i,t} \\
&+ \gamma_1 \times (CF/P)_{i,t} + \gamma_2 \times (E/P)_{i,t} + \gamma_3 \times (B/M)_{i,t} \\
&+ \lambda_1 \times \left| DA_{i,t} \right| + \lambda_2 \times DISP_{i,t} + \lambda_3 \times CRISIS_t + u_{i,t}, \quad u_{i,t} \sim N(0,\sigma).
\end{aligned}
$$

	Coefficient	S.D.	t-value	p-value
Const.	-0.093	0.015	-6.100	0.000
Technical analysis approach				
PRET	0.030	0.003	10.520	0.000
PVOL	0.003	0.001	4.150	0.000
Fundamental analysis approach				
CF/P	-0.063	0.009	-7.120	0.000
E/P	0.109	0.011	9.800	0.000
B/M	0.047	0.004	12.440	0.000
Determinant variables of optimal loadings				
|DA|	0.017	0.004	3.880	0.000
DISP	0.015	0.004	3.830	0.000
CRISIS	0.037	0.006	6.670	0.000
Error term in the regression				
SIGMA (σ)	0.2095	0.0008	261.875	0.000
Log-likelihood	4537.180			
AIC	4528.180			
Schwarz value	4490.575			

This table presents the estimation results of the model specification in which all the variables are employed as the explanatory variables for stock return. See Table1 for variable definitions and sample descriptions.
The statistics AIC = Log-likelihood function value – No. No. is the number of model parameters.
The statistics Schwarz value = Log-likelihood function value - (No./2) x ln(#). # is the number of sample.

Panel A: Technical Analysis (Regime I)



Panel B: Fundamental Analysis (Regime II)

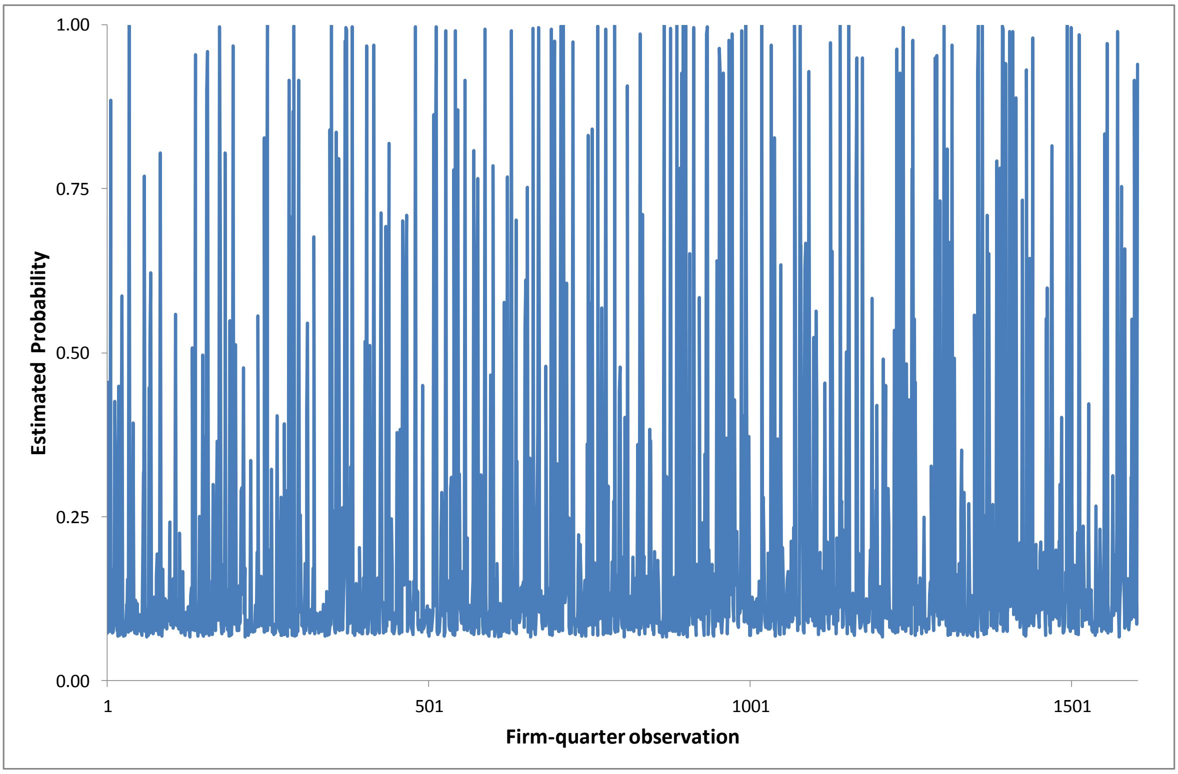
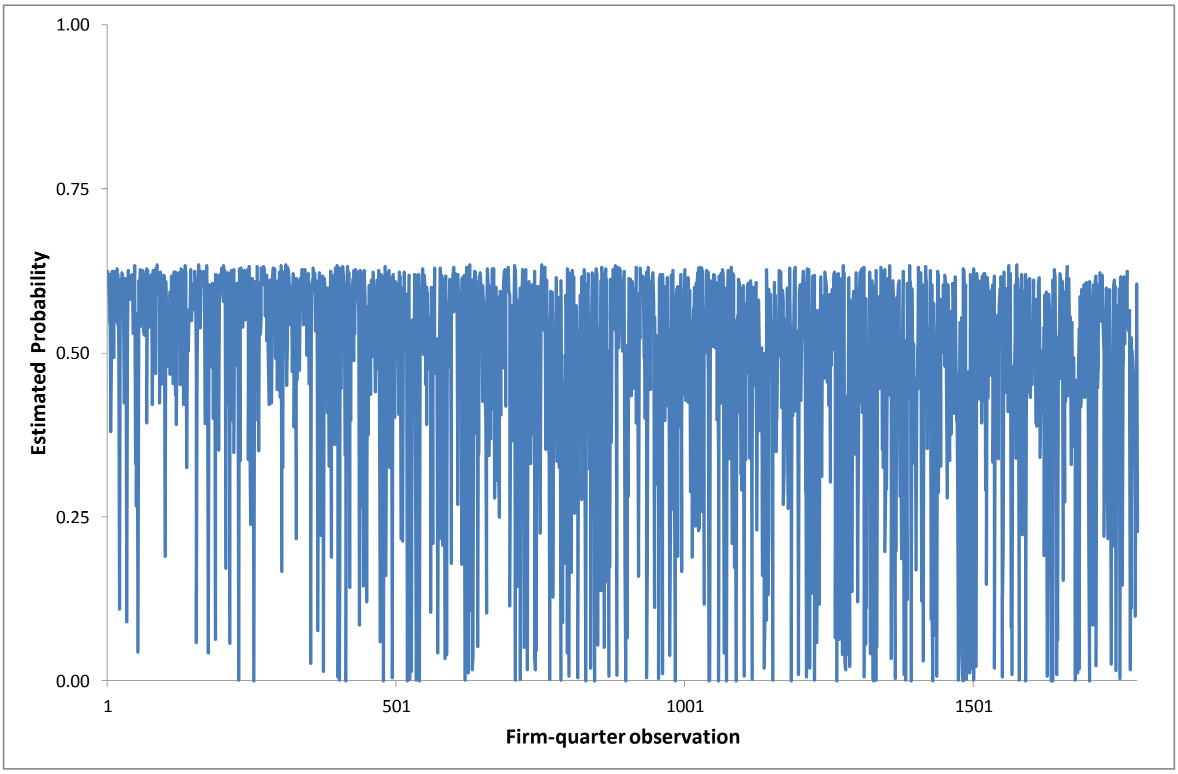


Figure 1: The estimated weights given to technical and fundamental analysis: Year 2009

Panel A: Technical Analysis (Regime I)



Panel B: Fundamental Analysis (Regime II)

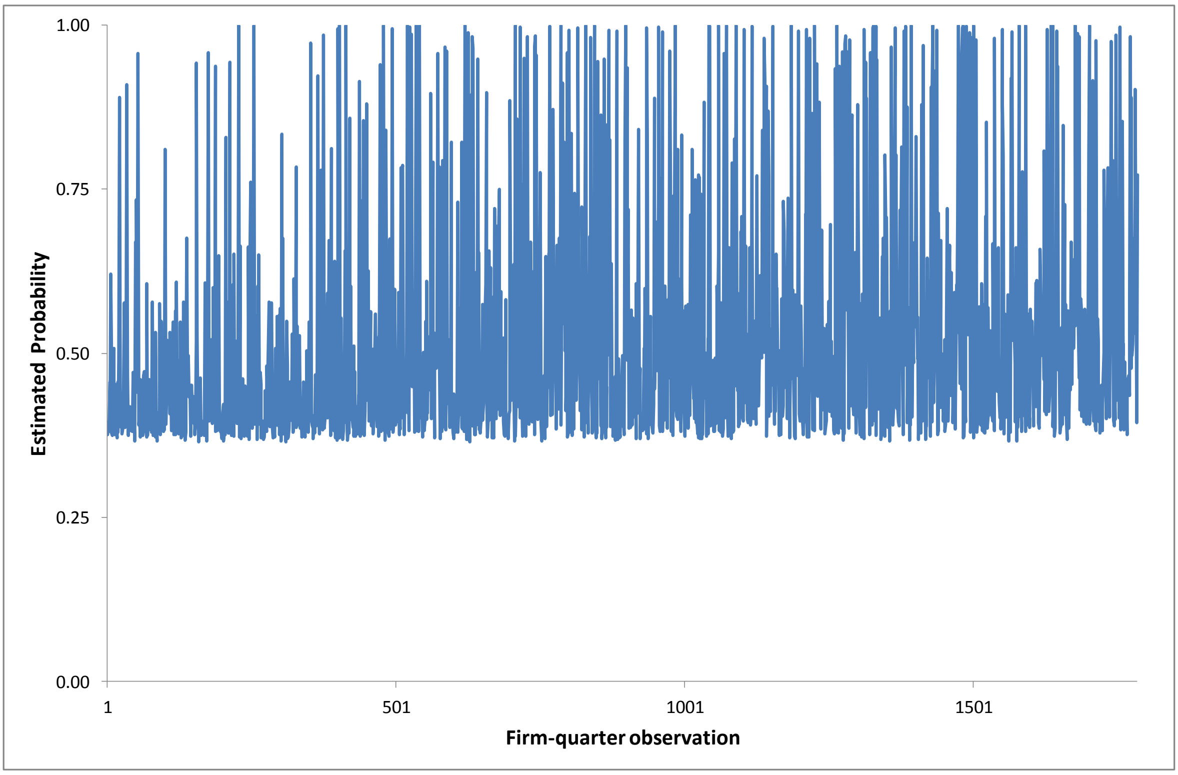


Figure 2: The estimated weights given to technical and fundamental analysis: Year 2015