Can Technical Analysis be used to Enhance Accounting Information based Fundamental Analysis in Explaining Expected Stock Price Movements?[1]

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Abstract

This paper provides new empirical evidence that price-based technical indicator variables can enhance the ability of accounting variables in explaining cross-sectional stock returns. We apply both OLS and state-space modelling to a sample of firms included in the Russell 3000 index over the period from 1999-2012 to compare the roles of the two main types of information typically used by stock investors. Empirical results reveal the importance of accounting variables over longer term horizons for particularly, small-cap stocks. Technical variables are shown to be important in the shorter term horizons. This result remains robust to alternative methodologies used.

JEL classification: G12; G14

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1. Introduction

In this paper, we investigate whether stock price based technical analysis can enhance the effectiveness of fundamental analysis in explaining stock price movements (SPM hereafter). We contribute new evidence to the ongoing debate on whether price-based or fundament-based equity valuation is more useful for equity analysts by using a state space modelling approach to avoid potential omitted variable bias which has long plagued the comparative analysis of these two alternative approaches to equity valuation. Our model includes a state variable, which represents an unobservable market wide common factor. We also investigate a firm size effect on the relative importance of accounting information on SPM by dividing our sample into two portfolios based on the market capitalization of the sample firms.

We have three major empirical findings. First, we show that combining both technical and fundamental analysis can better explain stock price movements, compared to the cases where technical or fundamental analysis is employed independently. This result has important implications to both academics and practitioners. Second, we uncover that the unobserved common factor provides statistically significant explanatory power for SPM. This supports the results of Duffie et al. (2009) in equity markets. Third, we find that there exists a significant size effect in the relative importance of the technical and fundamental variables.

Explaining and predicting SPM has for a long time attracted both academics and practitioners. There are two long-standing approaches to valuing stocks, fundamental and technical analysis. Fundamental analysts primarily use accounting information to study a company's underlying indicators of profit such as earnings, dividends, new products and R&D. On the other hand, technical analysts focus mainly on stock's own historical prices and returns. It is commonly accepted that technical analysis performs better in the short term while fundamental analysis is often believed to provide better estimates on long term intrinsic values (see for example, Taylor and Allen, 1992, Lui and Mole, 1998 and Amini et al., 2013).

Most of the existing literature has focused on one or the other aspect of SPM but not both. This may be the fundamental reason why cross-sectional stock returns cannot be satisfactorily explained. Fundamental and technical analysis or the intrinsic value and market value of a stock price should ideally be considered together in explaining SPM but surprisingly, there has been little attention placed on understanding their complementary roles. For example, a key assumption of the implied cost of capital approach (ICC) of Chen, Da and Zhao (2013) is that analyst earnings forecasts are timely reflections of the marginal investors' belief regarding future cash flows. This assumption could be met if and only if investors consistently update all available information in the market, including all past prices, demand and supply conditions as well as financial statements.

Therefore in this paper, we consider fundamental and technical analysis jointly to comprehensively investigate the effect of both aspects on SPM. Our work is close to that of Taylor and Allen (1992), Bonllinger (2005) and Bettman et al. (2009). However, we differentiate our study from earlier attempts by considering a richer set of technical indicators capturing price-based information over different time horizons alongside accounting variables. Importantly, we contribute a more accurate comparison of the explanatory power provided by accounting information-based and price-based technical indicators for stock price variations by accounting for common unobservable factors that may also influence stock prices.

For large companies that have many equity analysts following their stock, most of the fundamental factors should be incorporated into past stock prices. For small companies that do not have many analysts following the company, there exists greater information asymmetry with respect to the company's news. If it is good news that would push the stock price up, the executives of the company would actively spread the information while if it is bad news, the speed of information diffusion would be much slower. It is well documented that the degree of information diffusion is much faster for larger companies. (See Chae, 2005) Therefore, we expect that the explanatory power of fundamental factors on small-cap SPM would be more significant than that on large-cap stocks.

Hence in this paper, we address 3 main research questions. Are fundamental and technical analyses complementary rather than competitive in terms of their informativeness for SPM? Does fundamental analysis have more explanatory power for the movements in small cap stock prices than in large cap stock prices? And what is the relative importance of fundamental and technical variables in predicting future SPM over different investment horizons?

Although most active portfolio managers claim that they are interested in investing for the long term, stock price momentum continues to be one of the most frequently employed variables for trading strategies. In practice, momentum is fundamental to many active portfolio managers while the importance of accounting information is often neglected because its short term predictive ability for SPM is less accurate. Therefore, by showing that the use of accounting information as part of a fundamental approach to equity analysis can add value to standalone technical analysis, the empirical findings of this paper are useful for long-term investors and portfolio managers who are concerned with temporary deviations of stock prices from intrinsic values which can often arise. Our findings also have policy implications for regulators who are interested in the behavioral aspects of technical traders that can at times, move asset prices excessively within a short time.

This paper, in essence, decomposes the movements in stock prices into two broad types of factors, factors driven by accounting information and by technical analysis for a sample of large cap and small cap stocks listed on one of the world's largest exchanges, the New York Stock Exchange (NYSE). The contribution of this paper is as follows. The paper provides additional evidence that accounting variables are useful in explaining stock price movements over longer-term investment horizons. The paper decomposes SPM into factors that are driven by investors employing either technical or fundamental analyses. This allows us to investigate under what circumstances SPM may be strongly influenced by short-term investors who tend to use technical analysis based on daily share price fluctuations or long-term investors who tend to use fundamental analysis based on lower frequency accounting information. And the paper unambiguously shows that the greater information asymmetry regarding small-cap stocks influences the predictive power of accounting information over and above technical analysis, particularly over longer investment horizons.

The rest of the paper is organized as follows. Section 2 provides an overview of the relevant literature. Section 3 describes the data and approach used in our analyses whilst Section 4 discusses the empirical results. Finally, conclusions are provided in Section 5.

2. Fundamental Analysis vs. Technical Analysis

2.1. Fundamental Analysis

Fundamental analysts use accounting information to study a company’s underlying indicators. They investigate financial statements of the firm and its competitors in estimating the future evolution of the value of the company hence, its stock price movements. One of the major purposes of accounting practice is to help readers of financial statements forecast a company’s future cash flows (FASB, 1978). If the information on financial statements reflects the fundamental values, then the accounting information for a firm should explain a significant proportion of SPM. However, the literature so far yields mixed results in finding a link between stock performance and accounting measures.

Although a significant proportion of stock price movement occurs because investors revise their expectations of future cash flows, neither expected cash flows nor discount rates are observable and the traditional approach is to predict them and calculate cash flow news and discount rate news as functions of the predictive variables. As Chen, Da and Zhao (2013) note, there is a growing literature that shows, with different sample periods or cash flow measures, cash flow news can be more important than what has traditionally been shown (Ang and Bekaert 2007; Larrain and Yogo 2008; Chen 2009, Binsbergen and Koijen 2010; Chen, Da, and Priestley 2012). They use the prevailing market (consensus) earnings forecasts (from IBES) to back out the firm-specific implied cost of equity capital (ICC).

Both Ng, Solnik, Wu and Zhang (2013) and Chen, Da and Zhao (2013) show that accounting measures like revisions in analysts' consensus earnings forecasts can explain a large proportion of SPM over longer investment horizons compared to shorter horizons. This is consistent with Chen and Zhang (2007), who provide theory and evidence showing how accounting variables explain cross-sectional stock returns. Based on Zhang's (2000) framework used for linking equity value to accounting measures of underlying operations, they derive SPM as a function of earnings yield, equity capital investment, and changes in profitability, growth opportunities, and discount rates. Empirical results of their paper show that the accounting variables explain about 20% of the cross-sectional price variation.

The upside of fundamental analysis is that it has an intuitive link to SPM. It should, at least in theory, represent the long term, intrinsic value of a stock. However, the downside is that fundamental analysis is not capable of reflecting the short term movements in stock prices. There could be many reasons for this: quarterly reporting of financial reports or delays in operational processes to reflect new market conditions into earning's figures and so on. The most critical weakness of the fundamental analysis is that it does not accurately predict SPM, in general in the short term.

2.2. Technical Analysis

Technical analysts focus mainly on future stock prices given past patterns in stock price movements but they also take into account psychological aspects in the demand for a company's stock. Stock prices fluctuate tremendously from day to day. Technical analysts typically believe that past stock prices are good indicators of future SPM. Technical analysts form their expectation of future SPM based on the past price information or 'momentum' factors. They employ many techniques, including the use of charts. Using charts, technical analysts seek to identify price patterns and market trends in financial markets and attempt to exploit these patterns. Traders and portfolio managers continue to use technical analysis to formulate buy and sell decisions.

There is much academic interest in the effects of momentum on asset prices and recent studies include Grinblatt and Moskowitz (2003), Choria and Shivakumar (2006), Sadka (2006), Zhu and Zhou (2009), Marx (2012), Fama and French (2012), Moskowitz, Ooi and Pederson (2012), Bajgrowicz and Sxaillet (2012) and Menkhoff et al. (2012). Some earlier studies suggest that technical analysis beats the market in risk neutral terms, hence its popularity. One of the simplest and most widely used trading strategies based on technical analysis is the Moving Average (MA) rule. It is an objective rule-based trading strategy in which buy and sell signals are determined by the relative magnitudes of short and long term MAs. Extant studies based on MA rules include Acar and Satchell (1997), Chiarella, He and Hommes (2006) and Menkhoff (2010). The MA rule often leads investors to invest with or against the trend (ie., momentum) since it assumes that prices trend directionally. It takes advantage of price trends, captured as the gap between two MAs computed over different horizons.

The upside of technical analysis is that there is much evidence indicating that it can accurately predict short term movements in stock prices and the trade can be profitable (see Jegadeesh and Titman, 1993, 2001). This is because there is autocorrelation in stock price processes. (see Hong and Satchell, 2013) Moreover, it reflects the behavioral aspects of SPM. This may be another reason why technical analysis performs better than fundamental analysis in the short term.

However the downside is that it has no theoretical basis and merely explains the stylized facts in the market and investors' behavior. In particular, it is greatly influenced by herding behavior and the crowds do not necessarily predict SPM correctly. Another downside is that it only uses historical information and has no forward-looking aspect. This typically works against technical analysis when there are significant regime changes in the market conditions or in the macroeconomic trends. Technical variables, constructed based on the historical information, would not be able to foresee the movements that significantly deviate from the historical patterns.

2.3. Blending the Two

In short, fundamental analysts seek to determine the intrinsic value of the company while technical analysts tend to trade based on market forces such as the supply and demand of the stock concerned. We have seen that both approaches have their own advantages and limitations. Therefore it would be natural to assume that both fundamental and technical factors affect stock price movements. Existing studies that fail to draw a strong complementary relationship for both sets of determinants tend to focus only on the accounting side of the story. However, stock price momentum could be very noisy. Hence, omitting momentum related variables may obscure the more stable, long term relationship between SPM and accounting information. As such, this paper investigates whether and to what extent accounting and technical analyses could be complementary to each other for explaining SPM.

Although not applied to the equity market, one of the earliest works, reporting the complementary nature of technical and fundamental analyses is Taylor and Allen (1992). They argue that about 90% of foreign exchange market dealers rely on both technical and fundamental analyses. The four factor model of Cahart (1997) is also a good example of the complementary nature of technical and fundamental analyses. In that well accepted asset pricing model, Cahart (1997) shows momentum is significant in explaining mutual fund performance alongside Fama and French’s (1993) three factor model, which depends on accounting information (market capitalization and the book-to-market ratio) and the market risk premium.

Bettman, Sault and Schultz (2009) note that models simultaneously incorporating both fundamental and technical explanatory variables for equity prices are rarely used. They provide preliminary evidence to support that fundamental and technical variables could be complementary in explaining SPM, using US data from 1983 to 2002. However, they only include the 5 day lagged price, book value of the firm’s equity, diluted earnings per share and consensus forecast earnings per share to explain SPM. And the analysis relies on simple OLS. This paper extends and improves upon the extant literature by providing a more thorough and complete investigation with more appropriate and robust econometric techniques.

3. Data and Methodology

3.1. Data and Portfolio Construction

We base our analyses on all stocks in the Russell 3000 index that have monthly and quarterly data available in CRSP between January 1999 and December 2012. Since one of the main objectives of this paper is to separately investigate the explanatory power conditional on firm size, the sample coverage in the Russell 3000 index is more appropriate than other frequently used US equity indices such as the S&P500. As we use analysts long term earnings forecast from the Institutional Broker Estimate System (IBES) in this paper, this restricts the firm coverage in our sample. Our sample consists of all Russell 3000 index companies for which long term analyst earnings forecasts could be obtained from IBES. The sample we study comprise of firms with membership in the Russell 3000 index with data available from both CRSP and IBES databases. This leaves a total of 774 firms in the sample.

We follow Chen and Zhang (2007) and take the first consensus earnings forecast available for a given month to ensure that the growth opportunity measure impounds the current month's earnings information. This ensures that the forecast obtained for month *t* covers the long term forecast from month *t*. Chen and Zhang (2007) trim 0.5% of the extreme observations at the top and bottom ends of the distribution for each of the following variables. This practice systematically eliminates outliers in the sample period. Our data typically covers 144 time periods as we have 12 month lag variables. Hence the largest and the smallest 0.72 observations are subject to trimming. Hence the 0.5% trimming criteria is not appropriate with our current sample. Moreover, our sample period covers the 2007-2008 Global Financial Crisis. During financially distressed periods, the stock price co-movements increase due to the propagation of distress, which is typically associated with greater declines in market values (Berger and Pukthuanthong, 2012). More specifically, it is associated with the balance sheet contraction of individual firms. Such balance sheet contraction affects the accounting variables we employ in this paper and hence this is already effectively accounted for in the model. For these reasons, we use the entire sample without trimming any observations.

Table 1 shows the descriptive statistics of the sample data. The descriptive statistics of our sample data is comparable with those of Chen and Zhang (2007). Despite the difference in the sample period investigated, our summary statistics indicate that the aggregate portfolio level data that we examine is comparable to the firm level data used in Chen and Zhang (2007). We include Table 1 panel A and C of Chen and Zhang (2007) in Appendix 1, to facilitate this comparison.

(Insert Table 1 here)

The Russell 3000 index represents about 98% of all US equities by market value. Because of its broad diversification and large number of constituents, this index often makes for a popular alternative to a representative total market index such as the Wilshire 5000. The Wilshire 5000 index, which is considered to be the benchmark for U.S. total market returns, includes some stocks that are almost impossible to trade. The more stringent requirements for inclusion into the Russell 3000 index presents a better representation of the universe of actively traded stocks when compared to the Wilshire 5000 (See Russell Investments, 2013).

We follow the approach of Chen and Zhang (2007) in our sample construction but we differentiate our work with the use of stock portfolio-level analyses. Chen and Zhang use a pooled sample but this is not appropriate for our study as we also estimate a state space model. Hence, instead we construct stock portfolios based on firm size. To do this, all per share measures are multiplied by the number of shares outstanding (from IBES) to obtain the aggregated values at the individual firm level. This gives rise to a primary sample extending from 1999 to 2012 with 1,853,124 firm-month observations. We then construct two size portfolios based on the market capitalization of our sample firms around the median value with each comprising 387 firms. The first portfolio represents large cap stocks and the second portfolio represents small cap stocks. We refer to the large-size portfolio as portfolio 1 and the small-size one as portfolio 2.

The firm-level accounting data is available from the Compustat North America database and Thomson Reuters' Worldscope database. Stock prices are sourced from Bloomberg and earnings forecasts data are extracted from the Institutional Broker Estimate System (IBES). All accounting data are observed quarterly while stock prices are observed monthly.

As the accounting data is available at the quarterly frequency while stock price data is commonly studied at the monthly frequency, this creates a mixed-frequency problem. In order to overcome this, we need a precise understanding of the evolution of our quarterly data over unobserved periods. There are two different types of data in our sample, stocks and flows. Stock data are snapshots of the measured variable at a given point in time, whereas flow data represent an accumulation over a given period. Stock returns, profitability, growth opportunities and discount rates are stock variables but earnings yield and capital investments are flow variables. Monthly observations of flow variables could be cumulated over a quarter and become the end of the quarter observation. In reverse, this means that the end-of-quarter observations for flow variables can be decomposed into daily observations. However this does not apply to stock variables. Since all our quarterly observed variables are flow variables, weighted average is used under this assumption.

3.2. A Model of Equity Value and Stock Returns: Fundamental Analysis

This paper takes the equity valuation model of Zhang (2000) and follows Chen and Zhang (2007) in establishing the theoretical relationship between stock returns and accounting fundamentals. This section briefly introduces the equity valuation model that is detailed in

Chen and Zhang (2007).

The model measures the characteristics of underlying operations of a company using the links between the future cash flows and the observed accounting data in valuing equity. Equity value is a function of two basic operational attributes: scale and profitability, hence the value of a company amounts to forecasting the relative scale and profitability of future operations with respect to those on current operations. As expected, profitability (ROE) is a key measure in this model and it measures a firm's ability to generate value from the invested capital and indicates how the firm is likely to adjust its operations going forward. The advantage of this model is that it embeds the firm's value-creating capital investment decisions within the set of available opportunities as characterized by options to grow and to downsize or abandon. (See Berger et al., 1996 and Berk et al., 1999 for the links between real options and firm valuation.)

Let V_t be the value of an all equity-finance firm at date t. B_t is the corresponding book value of equity. X_t is the earnings generated in period t, and g_t is the firm's growth opportunities as perceived at t. g_t is defined as the percentage by which the scale of operations (capital invested) may grow. Let $q_t \equiv X_t / B_{t-1}$ as profitability (ROE) at time t. Let $E_t(X_{t+1})$ be the expected next-period earnings, k is the earnings capitalization factor, and $P(q_t)$ and $C(q_t)$ are the put option to abandon operations and the call option to expand operations, respectively. $P(q_t)$ and $C(q_t)$ are normalized by the scale of operations, B_t. To simplify the analysis, assumes that profitability follows a random walk, $\tilde{q}_{t+1} = q_t + \tilde{e}_{t+1}$. Chen and Zhang (2007) derives the valuation function of equity as

$$V_t = B_t\left[q_t / r_t + P(q_t) + g_t C(q_t)\right] \equiv B_t \upsilon(q_t, g_t, r_t) \tag{1}$$

where $\upsilon(q_t, g_t, r_t) \equiv q_t / r_t + P(q_t) + g_t C(q_t)$. This implies that the equity value can be decomposed into the amount of equity capital invested, B_t, and the value per unit of capital, υ, which is a function of profitability (q_t), growth opportunities (g_t), and the discount rate (r_t). Zhang (2000) shows that υ is an increasing and convex function of q_t.

Now consider ΔV_{t+1}, the change in equity value from date t to date t+1. Define $\upsilon_1 \equiv$ dυ/dq_t and $\upsilon_3 \equiv$ dυ/dr_t. dυ/dg_t is $E(q_t)$ and need not to be defined again. Let D_t be the dividends paid in period t+1. Chen and Zhang (2007) derive the period t+1 stock return, denoted R_{t+1} as

$$R_{t+1} = \left[\frac{X_{t+1}}{V_t}\right] + \upsilon_1\left[\frac{B_t}{V_t}\Delta q_{t+1}\right] + \left[\left(1 - \frac{B_t}{V_t}\right)\frac{\Delta B_{t+1}}{B_t}\right] + C(q_t)\left[\frac{B_t}{V_t}\Delta g_{t+1}\right] + \upsilon_1\left[\frac{B_t}{V_t}\Delta r_{t+1}\right] \quad (2)$$

Eq. (2) shows that the stock return is a function of the earnings yield, the change in profitability, the change in equity capital, the change in growth opportunities, and the change in the discount rate.

Based on the relationship represented in Eq. (2), Chen and Zhang (2007) run the following approximated regression.

$$R_{it} = \alpha + \beta x_{it} + \gamma \Delta \hat{q}_{it} + \delta \Delta \hat{b}_{it} + \omega \Delta \hat{g}_{it} + \varphi \Delta \hat{r}_{it} + e_{it} \quad (3)$$

where R_{it} is the annual stock return; $x_{it} = X_{it} / V_{it-1}$ is the earnings yield divided by the beginning-of-period market value of equity; $\Delta \hat{q}_{it} = (q_{it} - q_{it-1}) B_{it-1} / V_{it-1}$ is the change in profitability, adjusted by the beginning-of-period ratio of the book value of equity to the market value of equity, with profitability defined as the return on equity (ROE); $\Delta \hat{b}_{it} = [(B_{it} - B_{it-1}) / B_{it-1}](1 - B_{it-1} / V_{it-1})$ is capital investment, adjusted by one minus the beginning-of-period book-to-market ratio; $\Delta\hat{g}_{it} = (g_{it} - g_{it-1})B_{it-1}/V_{it-1}$ is the change in growth opportunities, adjusted by the beginning-of-period book-to-market ratio; $\Delta\hat{r}_{it} = (r_t - r_{t-1})B_{it-1}/V_{it-1}$ is the change in the discount rate, adjusted by firm's beginning-of-period book-to-market ratio. We take the five accounting variables in Eq. (3) as our fundamental variables for explaining stock price movements.

3.3. The Model: Enhancing with Technical Analysis

We define the stock price movements as price changes relative to initial price (without dividends) following the definition of Chen, Da and Zhao (2013). This is equivalent to capital gain returns. Therefore, for portfolio *i*, the one-period stock price movement from time *t* -1 to time *t* could be denoted as

$$\Delta p_{i,t} = \frac{p_{i,t+h} - p_{i,t}}{p_{i,t}} \tag{4}$$

where i = (1, 2). $\Delta p_{i,t}$ is the one period stock return. We classify two groups of variables: fundamental (i.e. accounting-based) variables and momentum (ie. price based) variables. Fundamental variables are those used in Chen and Zhang's (2007) valuation model and include earnings yield (*x*), equity capital investment (*Δb)*, changes in profitability (*Δq)*, growth opportunities (*Δg)*, and discount rates (*Δr)*. Technical variables include various return moving averages (*MAs*) over different measurement horizons. We include five lagged returns, lagged by 1, 3, 6, 9 and 12 months, and name them $T_{1M,i,t}$, $T_{3M,i,t}$, $T_{6M,i,t}$, $T_{9M,i,t}$ and $T_{12M,i,t}$, respectively.

The five lagged returns are selected to capture the short term, medium term and long term influence of technical variables.

We first examine the impact of having both fundamental and technical variables under the traditional OLS framework. Hence we run

$$\Delta p_{i,t} = \alpha + \beta_i F_{i,t} + \gamma_i T_i + \varepsilon_{i,t} \tag{5}$$

where $\beta_i = (\beta_{i,1} \quad \beta_{i,2} \quad \beta_{i,3} \quad \beta_{i,4} \quad \beta_{i,5})$, $\gamma = (\gamma_{i,1} \quad \gamma_{i,2} \quad \gamma_{i,3} \quad \gamma_{i,4} \quad \gamma_{i,5})$, $F_{i,t} = (x_{i,t} \quad \Delta q_{i,t} \quad \Delta b_{i,t} \quad \Delta g_{i,t} \quad \Delta r_{i,t})$, $T_{i,t} = (T_{1M,i,t} \quad T_{3M,i,t} \quad T_{6M,i,t} \quad T_{9M,i,t} \quad T_{12M,i,t})$

We first provide a directly comparable result to the existing literature explaining cross-sectional returns using our size portfolios by estimating Eq. (5) using OLS. Our preliminary check on the data reveals that the sample suffers from heteroskedasticity. This is resolved by using the Newey-West method of multiplying the inverse of the residual covariance matrix. This is equivalent to using the generalized least square (GLS) method.

While it is expected that the fundamental and technical variables will jointly explain a large proportion of SPM, there remains the possibility of omitted variable bias in Eq. (5). It is highly likely that there exists other factors causing stock prices to change and these factors are stochastic in nature. Hence, we aggregate these factors into one variable and estimate it using a Kalman filtering technique and name it *Z*. Having a conditioning variable, *Z*, in the regression has two advantages: (i) it ensures that our residual term is i.i.d. by reducing potential multicollinearity and omitted variable bias and (ii) it allows us to precisely quantify the level of incremental contribution to the predictive power of the model, which will be investigated in the next section. This will be further discussed in detail in Section 3.5.

Therefore we have

$$\Delta p_{i,t} = \alpha + \beta_i F_{i,t} + \gamma_i T_i + \lambda Z_t + \varepsilon_{i,t} \tag{6}$$

where all parameters and variables are as previously defined.

Running Eq. (6) yields the relationship between variations in stock prices and the fundamental and technical variables.

3.4. Estimation Method: State Space Model

Note that the variable *Z* does not have subscript *i* as *Z* will be estimated from both size portfolios simultaneously. Hence all portfolios share the same *Z*. This is equivalent to frailty in statistics (see Duffiee et al., 2009). As previously stated, a conditioning variable, *Z*, represents the market wide common stochastic factors that cause stock prices to change. Although used under a completely different framework, Goh et al. (2012) notes the importance of this type of variable and uses an equivalent approach and also refer to it as variable *Z*. In explaining bond risk premia using technical variables, Goh et al. (2012) includes an economic variable, *Z*, which includes macroeconomics factors from Ludvigson and Ng (2009). Instead, we apply a standard Kalman filtering technique to extract the same information from the market data.

Using a state space model ensures that we suffer less from omitted variable bias since it is not possible to include all variables that potentially affect stock price movements. Adopting a filtering approach in the estimation of a state space model also allows us to be less prone to an over-fitting problem. In implementing the state space model, we follow Hamilton (1994) closely. In this section, however, we describe and justify the structure of the state equation. Filtering also has major advantages over principal component analysis (PCA). First, filtering yields a more parsimonious regression model whilst allowing us to include more information. We must decide the number of components to include in a PCA and the criterion for this becomes ambiguous when the explanatory power of the first component is not sufficiently large. Many choose the number of PCs that can explain more than an arbitrary level of all movements in the underlying variables of interest (e.g. 90%) but this may require multiple PCs to be included in subsequent regression analyses.[3] Second, filtering allows us to project the common variable, *Z*, by giving it a structure. When using PCA, we cannot forecast the value of principal components. Therefore filtering is more appropriate for explaining future stock returns.

Under the assumption of linearity and multivariate Gaussian error terms, parameters of state equations estimated using Kalman filter are optimal. Eq. (7) is the observation equation, where we intend to estimate *Z* with the state equation. The state equation is modelled with an AR(1) process.

$$Z_t = \rho Z_{t-1} + \sqrt{1-\rho^2}\,\omega_t \tag{7}$$

where $-1 < \rho < 1$. *Z* is a factor that includes commonalities of the sample portfolios. Therefore *Z* represents macroeconomic and financial market conditions that commonly affect the US equity market. This statement is almost true because our sample, Russell 3000 stocks, represents approximately 98% of the investable equities in US stock markets. By including *Z*, we are controlling for unobserved macroeconomic, market wide variability that is known to exist. It is well known that macroeconomic factors are cyclical, therefore, *Z* is modelled by

[3] For example, Pukthuanthong and Roll (2009) use the first 10 principal components from a PCA to explain country-level stock index returns at the daily frequency.

AR(1) process, where 1 period is one quarter, consistent with the data interval of the fundamental variables. The parameter ρ would represent the cyclicality of the variable Z.

If we employ a simple AR(1) process of $Z_t = \rho Z_{t-1} + \omega_t$, the state equation will introduce an identification problem. Parameters, β, γ, λ and ρ, are estimated by iteratively maximizing the likelihood function where the state variable Z is unobserved. The same values of the likelihood function could be obtained with various combinations of the λ and Z, as long as the multiples of the two are the same. Controlling for the conditional variance of Z can correct this identification problem. Therefore we impose a constraint that the conditional variance of Z is equal to 1. This is equivalent to performing a GLS estimation of the state equation. The proof is in Appendix 2. Once we filter the state variable Z and forecast one period ahead for Z using the state equation.

If Z properly represents the market wide common shock, our ex-ante expectation of λ is positive and significantly different from zero. ρ is expected to take a positive value while its statistical significance cannot be predicted. Cyclicality in market wide shocks could be absorbed in the technical variables.

For convenience, we will refer to these models as follow, hereafter.

OLSF Model: $\Delta p_{i,t} = \alpha + \beta_i F_{i,t} + \varepsilon_{i,t}$ (8)

OLST Model: $\Delta p_{i,t} = \alpha + \gamma_i T_{i,t} + \varepsilon_{i,t}$ (9)

OLSTF Model: $\Delta p_{i,t} = \alpha + \beta_i F_{i,t} + \gamma_i T_{i,t} + \varepsilon_{i,t}$ (10)

State Space Model: $\Delta p_{i,t} = \alpha + \beta_i F_{i,t} + \gamma_i T_{i,t} + \lambda Z_t + \varepsilon_{i,t}$ (11)

4. Empirical Results

4.1. Fundamental Analysis with Technical Analysis under OLS Specification

The extant literature investigating the impact of accounting information and/or technical variables typically use OLS (See inter alia, Chen and Zhang, 2007, Bettman, Sault and Schultz 2009, Binsbergen and Koijen, R. 2010, Bajgrowicz and Sxaillet, 2012). In this section, we combine the fundamental variables suggested by Chen and Zhang (2007) and various technical indicators following the traditional OLS approach and compare the results to the cases when separate regressions are employed, i.e we are comparing the result of OLSF in Eq. (8) ($\Delta p_{i,t} = \alpha + \beta_i F_{i,t} + \varepsilon_{i,t}$) and OLST in Eq. (9) ($\Delta p_{i,t} = \alpha + \gamma_i T_i + \varepsilon_{i,t}$) to OLSFT in Eq. (10) ($\Delta p_{i,t} = \alpha + \beta_i F_{i,t} + \gamma_i T_i + \varepsilon_{i,t}$).Table 2 reports the results of OLSF and OLST and Table 3 reports the results of OLSFT.

(Insert Table 2 here)

(Insert Table 3 here)

In comparing OLS results presented in Tables 2 and 3 we note several striking results. When technical indicators are used in standalone regressions in Table 2, they are much less effective than when they are used alongside accounting information in Table 3. For instance, for large cap stocks in Panel A, the longer term technical variables, T_{6M} and T_{12M} are only mildly significant at the 10% level whilst for small cap stocks in Panel B, T_{3M} is the only statistically significant technical variable. This suggests that there is limited power in using technical analysis alone and that it is beneficial to use a combination of fundamental and technical variables when explaining stock price movements.

The R^2 of the small cap portfolio is larger than that of the large cap portfolio. This is consistently shown in all of later empirical models where we include both the fundamental and technical variables under OLS and state space model. This is consistent with our ex-ante expectation that

It can be seen in Table 3 that when fundamental and technical variables are used jointly to explain stock return variations, the adjusted R^2 significantly increases indicating that technical variables do provide substantial incremental information for explaining SPM over fundamental variables. This evidence suggests that there is a complementary role for the two types of security analyses. When they are used jointly in an OLS estimation, the statistical significance of some of the coefficients improve from when they are estimated separately. For instance, the estimates for the technical indicators T_{1M}, T_{3M}, T_{6M}, T_{9M} and T_{12M} all improve for the large-cap portfolio whilst the estimates for both fundamental and technical variables, Δb, Δg, T_{1M}, T_{6M}, T_{9M} and T_{12M} improve for the small-cap portfolio.

Our OLS results affirm the extant literature. The explanatory power of the our OLS models (measured by R^2 and the adjusted R^2 values) are comparable to those of Bettman et al. (2009). They report R^2 of 0.429 when only accounting fundamentals are regressed (Table 4 of Bettman et al, 2009) and adjusted R^2 of 0.7686 when fundamental and technical variables are combined (Table 5 of Bettman et al, 2009). All variables are significant in the expected direction.

While our results are fairly consistent with the extant literature, we show with the use of technical variables representing information over different time horizons that the coefficient of the one month lagged return, T_{1M}, is positive for both size portfolios when only technical variables are used to explain SPM. However, they become negative and also statistically significant when the model is augmented with fundamental variables. This suggests that some of the short term momentum could be captured by accounting information and the two types of variables have some overlap in their informativeness.

Taken together, the evidence suggests that the two sets of variables are complementary in nature rather than substitutes for one another. However, it should be noted that whilst the OLS results do not suffer from serial correlation or heteroskedasticity as they are controlled with the Newey-West method, the residuals from Eq. (10) do reject the Ramsey Regression Equation Specification Error Test (RESET). This suggests that the standard OLS model may be suffering from omitted variable bias.[4]

4.2. State Space Modelling

To overcome omitted variable bias, we next use a state space model specified by Eqns. (6)-(7). The results are provided in Table 4.

(Insert Table 4 here)

In Table 4, we observe that the coefficient of the latent variable is statistically significant and positive in explaining the returns of both size portfolios. Furthermore, the latent variable provides incremental explanatory power for variations in monthly SPM as the adjusted R^2 is higher when it is included alongside the fundamental and technical variables. Take together this evidence indicates that the latent variable is indeed important for picking up those unobservable common factors that influence SPM and that the OLS models that have been used in the extant literature suffer from omitted variable bias. Hence, prior studies have not provided an accurate picture of the relative importance of fundamental and technical analyses for security pricing.

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[4] The Ramsey RESET provides a general specification test on the linear regression model for whether non-linear combinations of the fitted values help to explain the response variable. The test is one of the most popular proxy tests for the omitted variable bias.

The state space model is well specified and more appropriate for modelling stock price movements as it yields non-serially correlated homoscedastic residuals with the latent variable Z_t, designed to absolve most of non-i.i.d. aspects of stock returns. Nonetheless, the state space model does not alter the signs of the estimated coefficients that are statistically significant in the combined OLSFT model. Duffie et al. (2009) also finds statistically significant unobserved market wide factor in suggesting a more realistic model of the risk of large default losses. Our finding may be considered its equivalent in equity market return.

4.3. Firm Size Analysis

The unobserved common factor has a significant and positive impact on the returns of both the large-cap and the small-cap companies but has a notably larger impact on the stock returns of the latter. This indicates that small cap stocks are more prone to market wide shocks.

In general, we find that larger firms tend to be more sensitive to accounting-based information. First, the performance of large-cap stocks is more dependent on earnings. Earnings exerts a greater economic impact on the stock returns of large firms relative to smaller firms as one standard deviation increase in earnings yield (x) would increase larger firms' monthly stock returns by 1.176% but only by 0.345% for smaller firms.

Second, changes in investment (Δb) have significant effects on large cap firms' stock performance but not on the small cap firms. One standard deviation increase in investment made can increase monthly stock returns by 0.269% in large firms but only 0.14% in small firms. This corroborates with evidence that the more significant investments made by large-cap companies tends to have greater impact on their performance.

Third, revisions in analyst's long term earnings forecasts (Δg) have much higher impact on large cap stock returns as one standard deviation increase in the long term growth forecasts can increase stock returns by 0.713% and 0.187% for large and small firms, respectively. This is because analysts tend to make much more accurate forecasts on the future performance of the large cap companies as information is more readily available to analysts. Also, trading of large cap stocks tends to be driven more by stock analysts' recommendations so it is expected that analyst earnings forecasts would provide more explanatory power for stock performance.

In contrast, changes in monthly profitability (Δq) are not significantly related to large cap stock performance but are important for explaining small cap stock returns. This is consistent with the notion that the stock returns of larger companies are less sensitive to the short term swings in company profits.

We note that larger firms are also more sensitive to technical variables as all momentum variables are significant for the large cap stocks, while the six month lag return (T_{6M}) is not significant for explaining variations in small cap stock returns. This suggests that in the medium term, price-based information is not so importance for smaller stocks relative to fundamental information.

Fourth, changes in the discount rate (Δr) have statistically significant negative influence on both portfolios' returns. It has much higher impact on small cap stock returns as one standard deviation increase in the discount rate change can decrease stock returns by 1.039% and 1.658% for large and small firms, respectively. The negative relationship meets the common expectation and is consistent with Chen and Zhang (2007). The larger impact on small firms is also intuitive as smaller companies are more prone to changes in discount rates. For example, small companies more likely to experience liquidity squeeze when the discount rate increases.

The intercept captures the mean return on a given stock portfolio. We note that the intercept is negative and significantly different from zero for large cap stocks while it is not statistically significant for the small cap stocks. This result is consistent with Fama and French (1993) where they find that small cap and value portfolios have higher expected returns — and arguably higher expected risk — than those of large cap and growth portfolios, all other things being held equal.

4.4. Robustness Checks

OLSFT model is a benchmark model that we use to assess the new evidence that can be gleaned from an alternative state space modelling approach. We find that the signs and the statistical significance of the estimated parameters are consistent with the OLSFT model. Compared with the benchmark model, the state space model offers higher explanatory power. Furthermore, the residual of the state space model is less likely to suffer from the omitted variable bias problem.

Next, we test the state space model over various subsample periods. The results for this subsection are not tabulated for brevity but are available upon request. The adjusted R^2 of the model remains steady as subsample period changes, ranging from 0.797, in 2000-2012, to 0.886, in 2004 – 2012.

Finally, we follow Chen and Zhang (2007) in verifying the robustness of the results obtained from the state space model and analyze various partitions of the sample. We partition the sample companies into quartiles based upon market capitalization. We run separate regressions for the four size portfolios. The results show that for all size quartiles, the regression coefficients have the same signs as predicted by the theoretical model, suggesting that the qualitative results presented are robust across different groupings for firm size.

(Insert Table 5 here)

5. Concluding Remarks

In this paper we revisit the relative importance of fundamental and technical analyses for stocks. We study a sample of the constituents of the Russell 3000 index from the US over the period from 1999-2012. Using a portfolio level analysis, we consider the differences in the explanatory power of the two main types of predictors for monthly stock price movement. In order to avoid potential omitted variable bias and to improve the explanatory power of our empirical model, we employ a state space model. Our model includes a state variable, which represents an unobservable market wide common factor.

We find that combining fundamental analysis with technical analysis can substantially enhance the explanation of stock price movements, compared to the cases where technical or fundamental analysis is employed independently. The adjusted R^2 significantly increases when the both variables are included in the estimation model.

We also find that the unobserved common factor has statistically significant explanatory power for SPM. Lastly, we find that there exists a significant size effect in the impacts of the technical and fundamental variables. Also we find that the adjusted R^2 increases when the common factor is taken into account indicating improved explanatory power for SPM.

Large cap stock returns are more sensitive to earnings, change in the investments and change in the long term growth expectations than small stocks returns. Returns of small cap stocks are more sensitive to change in profitability and change in discount rate. Both large cap and small cap stock returns are significantly explained by their own past values. The intercept, which captures the mean return on a given stock portfolio, is negative and significantly different from zero for large cap stocks while it is not statistically significant for the small cap stocks. This may indicate that that small cap and value portfolios have higher expected returns — and arguably higher expected risk — than those of large cap and growth portfolios and is consistent with Fama and French (1993).

The contribution of our paper to the extant literature can be summarized as follows. We empirically find that blending technical and fundamental analysis is beneficial in explaining stock price movements. However there exists a systematic portion in residual stock price movements that cannot be explained by the two and this factor must be extracted and segregated in order to have a better specified model. Once all these are taken into account, we find that there is a significant size effect. The fundamental variables, technical variables and unobserved common factor all have different impacts on stock price movements depending on the size of the companies.

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Tables and Figures.

Table 1.

Descriptive statistics of the sample

This table reports the descriptive statistics of the following variables. The portfolio return (R_t) is the monthly return of both portfolio; earnings yield (x_t) is earnings (X_t) divided by the beginning-of-period market value of equity (V_{t-1}); profitability change (dq_{it}) is month t profitability q_t minus month t-1 profitability q_{t-1}, where $q_t = X_t/B_{t-1}$ multiplied by B_{it-1}/V_{it-1}; capital investment ($\Delta B_{it}/B_{it-1}$) is the change in the book value of equity relative to the prior month scaled by beginning-of-period book value multiplied by B_{it-1}/V_{it-1}; growth opportunity change (dg_{it}) is the change in the median analyst forecast of the long-term growth rate following the current year earnings announcement relative to that of the prior year; the adjusted growth opportunity change is growth opportunity change multiplied by B_{it-1}/V_{it-1}; discount rate change (dr_{it}) is the change of the 10-year US Treasury bond yield over the return period multiplied by B_{it-1}/V_{it-1}. The sample consists of 774 firm-year observations over the period 1999–2012.

Panel A1: Monthly descriptive statistics of the total sample

Total Sample	Mean	Median	Std dev	Min	1st quartile	3rd quartile	Max
Portfolio Return	0.36%	0.82%	4.59%	-16.85%	-1.98%	3.20%	10.23%
Earnings yield (x)	0.06	0.07	0.03	-0.12	0.05	0.07	0.10
Profitability change (dq) (%)	0.00%	0.02%	2.27%	-13.12%	-0.66%	0.66%	10.76%
Capital investmnt (db) (%)	0.51%	0.52%	0.60%	-2.18%	0.25%	0.85%	1.80%
Growth opportunity change (dg) (%)	0.23%	0.23%	0.62%	-2.52%	-0.04%	0.51%	2.13%
Discount rate change (dr) (%)	0.11%	0.00%	1.33%	-8.67%	-0.32%	0.48%	6.06%
B/M ratio	0.34	0.33	0.10	0.17	0.28	0.43	0.61

Panel A2: Correlation matrix of the total sample

Correlation Matrix	R	x	dq	db	dg
Earnings yield (x)	0.28				
Profitability change (dq) (%)	0.11	0.22			
Capital investmnt (db) (%)	0.23	0.24	0.34		
Growth opportunity change (dg) (%)	0.11	0.09	-0.06	-0.12	
Discount rate change (dr) (%)	-0.16	-0.37	0.21	-0.14	-0.03

Table 2.

Estimated results of $\Delta p_{i,t} = \alpha + \beta_i F_{i,t} + \varepsilon_{i,t}$ and $\Delta p_{i,t} = \alpha + \gamma_i T_{i,t} + \varepsilon_{i,t}$.

This table reports the estimation results for Eq.s (8) and (9) in explaining monthly stock price movements of all sample stocks in the Russell 3000 index. Panel A shows the results for the large-size portfolio, portfolio 1, whilst Panel B reports results for the small-size portfolio, portfolio 2. OLS Fundamentals reports OLSF model in Eq.s (8) and OLS Technicals reports OLST model in Eq.s (9). R^2 and Adj R^2 rows report the R^2 and the adjusted R^2 of the regression models. Variable *x* is earnings divided by the beginning-of-period market value of equity; variable Δq is profitability change; capital investment, variable Δb, is the change in the book value of equity relative to the prior month; growth opportunity change, variable Δg, is the change in the median analyst forecast of the long-term growth rate; variable Δd is the discount rate (10-year US Treasury bond yield) change over the return period. $T_{1M,i,t}$, $T_{3M,i,t}$, $T_{6M,i,t}$, $T_{9M,i,t}$ and $T_{12M,i,t}$ are the lagged returns of the portfolio *i*, lagged by 1, 3, 6, 9 and 12 months, respectively. The sample consists of 774 firm-year observations over the period 1999–2012.

*, **, *** denote significance at the 10, 5 and 1% level of significance, respectively.

Panel A							
OLS Fundamentals				OLS Technicals			
Variable	Estimated Coeff	t-stat	p-value	Variable	Estimated Coeff	t-stat	p-value
x	0.263***	4.89	0.000	T_{1M}	0.346***	4.74	0.000
Δq	0.016	0.13	0.900	T_{3M}	0.097	1.41	0.162
Δb	0.760***	4.57	0.000	T_{6M}	-0.117*	-1.83	0.069
Δg	1.710***	2.87	0.005	T_{9M}	-0.055	-0.93	0.356
Δr	-0.825***	-3.67	0.000	T_{12M}	-0.097*	-1.66	0.098
constant	-0.019***	-5.2	0.000	constant	0.002	1.33	0.186
R^2	0.420			R^2	0.212		
Adj R^2	0.402			Adj R^2	0.186		

Panel B							
OLS Fundamentals				OLS Technicals			
Variable	Estimated Coeff	t-stat	p-value	Variable	Estimated Coeff	t-stat	p-value
x	0.093***	3.06	0.003	T_{1M}	0.110	1.43	0.156
Δq	0.214**	2.01	0.047	T_{3M}	0.128*	1.77	0.079
Δb	0.321	0.98	0.328	T_{6M}	-0.001	-0.01	0.994
Δg	0.304*	1.96	0.051	T_{9M}	-0.042	-0.64	0.521
Δr	-1.244***	-5.96	0.000	T_{12M}	-0.023	-0.36	0.716
constant	0.002	1.04	0.302	constant	0.002	0.86	0.392
R^2	0.454			R^2	0.046		
Adj R^2	0.437			Adj R^2	0.014		

Table 3.

Estimated results of $\Delta p_{i,t} = \alpha + \beta_i F_{i,t} + \gamma_i T_{i,t} + \varepsilon_{i,t}$.

This table reports the estimation results for Eq. (10) Panel A shows the results for the large-size portfolio, portfolio 1, whilst Panel B reports results for the small-size portfolio, portfolio 2. OLS Fundamental & Technical indicates OLSFT model in Eq.s (10). R^2 and Adj R^2 rows report the R^2 and the adjusted R^2 of the regression models. Variable x is earnings divided by the beginning-of-period market value of equity; variable Δq is profitability change; capital investment, variable Δb, is the change in the book value of equity relative to the prior month; growth opportunity change, variable Δg, is the change in the median analyst forecast of the long-term growth rate; variable Δd is the discount rate (10-year US Treasury bond yield) change over the return period. $T_{1M,i,t}$, $T_{3M,i,t}$, $T_{6M,i,t}$, $T_{9M,i,t}$ and $T_{12M,i,t}$ are the lagged returns of the portfolio i, lagged by 1, 3, 6, 9 and 12 months, respectively. The sample consists of 774 firm-year observations over the period 1999–2012.

*, **, *** denote significance at the 10, 5 and 1% level of significance, respectively.

Panel A				Panel B			
OLS Fundamental & Technical				OLS Fundamental & Technical			
Variable	Estimated Coeff	t-stat	p-value	Variable	Estimated Coeff	t-stat	p-value
x	0.393***	11.14	0.000	X	0.106***	5.87	0.000
Δq	-0.023	-0.29	0.769	Δq	0.205***	3.54	0.001
Δb	0.544***	5.82	0.000	Δb	0.313*	1.74	0.084
Δg	1.571***	4.49	0.000	Δg	0.428***	5.25	0.000
Δr	-0.809***	-6.95	0.000	Δr	-1.204***	-11.27	0.000
T_{1M}	-0.164***	-3.17	0.002	T_{1M}	-0.156***	-3.70	0.000
T_{3M}	0.110***	2.81	0.006	T_{3M}	0.073**	1.99	0.049
T_{6M}	-0.134***	-3.54	0.001	T_{6M}	-0.017	-0.51	0.611
T_{9M}	-0.096***	-2.94	0.004	T_{9M}	-0.073**	-2.24	0.026
T_{12M}	-0.064**	-2.03	0.044	T_{12M}	-0.062**	-2.02	0.045
constant	-0.026***	-11.14	0.000	constant	0.000	0.15	0.879
R^2	0.782			R^2	0.796		
Adj R^2	0.767			Adj R^2	0.782		

Table 4.

Estimated results of the state space model.

This table reports the estimation results from the state space model (represented in Eqs (6)-(7)) for explaining monthly stock price movements of all sample stocks in the Russell 3000 index. The sample period used is from January 1999 to December 2012. Panel A shows the results for the large-size portfolio whilst Panel B reports results for the small-size portfolio. Panel C shows the results for the model specification with only the inclusion of the latent factor, *Z*. Panel A and B include the estimated results of Eq.s (6) and Panel C includes the estimate result of Eq.s (7). OLS Fundamental & Technical indicates OLSFT model in Eq.s (10). Adj R^2 rows reports the adjusted R^2 equivalent for the OLSFT model. Variable *Z* is the unobserved factor that is shared by the both portfolios, extracted from the state space model; variable *x* is earnings divided by the beginning-of-period market value of equity; variable Δq is profitability change; capital investment, variable Δb, is the change in the book value of equity relative to the prior month; growth opportunity change, variable Δg, is the change in the median analyst forecast of the long-term growth rate; variable Δd is the discount rate (10-year US Treasury bond yield) change over the return period. $T_{1M,i,t}$, $T_{3M,i,t}$, $T_{6M,i,t}$, $T_{9M,i,t}$ and $T_{12M,i,t}$ are the lagged returns of the portfolio *i*, lagged by 1, 3, 6, 9 and 12 months, respectively. The sample consists of 774 firm-year observations over the period 1999–2012.

*, **, *** denote significance at the 10, 5 and 1% level of significance, respectively.

Panel A				Panel B			
Variable	Estimated Coeff	z-stat	p-value	Variable	Estimated Coeff	z-stat	p-value
Z	0.006***	2.94	0.003	Z	0.009***	2.94	0.003
x	0.392***	12.75	0.000	x	0.115***	7.41	0.000
Δq	0.001	0.01	0.988	Δq	0.224***	4.91	0.000
Δb	0.449***	5.98	0.000	Δb	0.233*	1.66	0.097
Δg	1.151***	4.29	0.000	Δg	0.302***	4.84	0.000
Δr	-0.781***	-6.99	0.000	Δr	-1.257***	-12.86	0.000
T_{1M}	-0.113**	-2.48	0.013	T_{1M}	-0.141***	-3.42	0.001
T_{3M}	0.108***	3.04	0.002	T_{3M}	0.068**	2.13	0.033
T_{6M}	-0.157***	-4.90	0.000	T_{6M}	-0.044	-1.50	0.134
T_{9M}	-0.067**	-2.37	0.018	T_{9M}	-0.065**	-2.38	0.017
T_{12M}	-0.067**	-2.48	0.013	T_{12M}	-0.056**	-2.14	0.032
constant	-0.025***	-12.39	0.000	constant	0.001	0.70	0.486
Adj R^2	0.7674			Adj R^2	0.7845		

Panel C			
Z	-0.136	-1.32	0.187

Table 5.

Robustness check with quartile portfolios.

This table reports the estimation results from the OLS model for quartile portfolios for explaining monthly stock price movements of all sample stocks in the Russell 3000 index. The sample period used is from January 1999 to December 2012. Panel A shows the results for the first quartile portfolio, Panel B reports results for the second quartile portfolio, Panel C reports results for the third quartile portfolio and Panel D reports results for the last quartile portfolio. Variable x is earnings divided by the beginning-of-period market value of equity; variable Δq is profitability change; capital investment, variable Δb, is the change in the book value of equity relative to the prior month; growth opportunity change, variable Δg, is the change in the median analyst forecast of the long-term growth rate; variable Δd is the discount rate (10-year US Treasury bond yield) change over the return period. $T_{1M,i,t}$, $T_{3M,i,t}$, $T_{6M,i,t}$, $T_{9M,i,t}$ and $T_{12M,i,t}$ are the lagged returns of the portfolio i, lagged by 1, 3, 6, 9 and 12 months, respectively. The sample consists of 774 firm-year observations over the period 1999–2012.
*, **, *** denote significance at the 10, 5 and 1% level of significance, respectively.

Panel 1	Portfolio 1		
Variable	Estimate Coeff	t-stat	p-value
x	0.3958***	13.14	0.0000
dq	0.1170**	2.15	0.0330
db	0.2590***	4.17	0.0000
dg	0.0257	0.09	0.9290
dr	-0.0233	-0.23	0.8190
T_{1M}	-0.0924	-1.64	0.1030
T_{3M}	0.0076	0.19	0.8520
T_{6M}	-0.1075***	-3.00	0.0030
T_{9M}	-0.0644*	-1.88	0.0620
T_{12M}	-0.0237	-0.77	0.4420
costant	-0.0249***	-12.44	0.0000
R^2	0.7191		
Adj R^2	0.6998		

Panel 2	Portfolio 2		
Variable	Estimate Coeff	t-stat	p-value
x	0.1195***	5.98	0.0000
dq	0.0302	0.87	0.3840
db	0.1786***	2.85	0.0050
dg	0.1867***	4.68	0.0000
dr	0.4758***	3.25	0.0010
T_{1M}	0.0536	0.55	0.5810
T_{3M}	-0.2996***	-4.12	0.0000
T_{6M}	-0.0297	-0.47	0.6390
T_{9M}	0.0609	1.04	0.3020
T_{12M}	0.0713	1.32	0.1900
costant	0.0012	0.85	0.3980
R^2	0.4112		
Adj R^2	0.3706		

Panel 3		Portfolio 3	
Variable	Estimate Coeff	t-stat	p-value
x	0.0947***	3.4800	0.0010
dq	0.0405	0.63	0.5320
db	-0.0600	-0.48	0.6320
dg	0.0429	1.25	0.2140
dr	0.3365	1.63	0.1050
T_{1M}	0.1532	1.19	0.2340
T_{3M}	-0.1327	-1.61	0.1100
T_{6M}	-0.0412	-0.55	0.5850
T_{9M}	0.0298	0.44	0.6640
T_{12M}	0.0521	0.81	0.4210
costant	0.0045**	2.16	0.0320
R^2	0.1418		
Adj R^2	0.0826		

Panel 4	Portfolio 4		
Variable	Estimate Coeff	t-stat	p-value
x	0.0688***	5.38	0.0000
dq	0.2328***	3.32	0.0010
db	0.1014	0.55	0.5830
dg	0.0566***	3.77	0.0000
dr	0.3048	1.60	0.1110
T_{1M}	0.0178	0.16	0.8730
T_{3M}	-0.0905	-1.17	0.2430
T_{6M}	-0.2132***	-3.05	0.0030
T_{9M}	-0.0500	-0.76	0.4500
T_{12M}	0.0847	1.30	0.1970
costant	0.0125***	4.27	0.0000
R^2	0.3269		
Adj R^2	0.2805		

Appendix.

Appendix 1. Descriptive Statistics of the data in Chen and Zhang (2007)

Panel A1: Descriptive statistics of the pooled sample

Portfolio Total	Mean	Median	Std dev	Min	1st quartile	3rd quartile	Max
Portfolio Return	0.15	0.10	0.43	-0.78	-0.12	0.35	2.73
Earnings yield (x)	0.06	0.07	0.08	-1.39	0.04	0.09	0.49
Profitability change (dq) (%)	-1.55	-0.01	14.53	-143.20	-5.61	3.14	149.47
Capital investmnt (db) (%)	0.13	0.10	0.27	-0.91	0.2	0.19	4.40
Growth opportunity change (dg) (%)	-0.53	-0.09	3.74	-55.00	-1.60	0.74	47.00
Discount rate change (dr) (%)	-0.29	-0.51	1.18	-4.34	-1.04	0.61	3.18
B/M ratio	0.59	0.53	0.35	0.01	0.34	0.76	4.43

Panel A2: Correlation matrix of the total sample

Correlation Matrix	R	x	dq	db	dg
Earnings yield (x)	0.29				
Profitability change (dq) (%)	0.29	0.45			
Capital investmnt (db) (%)	0.24	0.33	0.26		
Growth opportunity change (dg) (%)	0.23	0.09	0.16	0.07	
Discount rate change (dr) (%)	-0.13	0.00	0.05	0.00	0.02

Note that Chen and Zhang (2007) use annual data while we use monthly data. Also they collect the annual stock return from 2 days after the year *t*-1 earnings announcement to one day after the year *t* earnings announcement.

Appendix 2. Conditional Variance of Equation (7)

$$Z_t = \rho Z_{t-1} + \sqrt{1-\rho^2}\,\omega_t$$

$$Z_t = \rho\left(\rho Z_{t-2} + \sqrt{1-\rho^2}\,\omega_{t-1}\right) + \sqrt{1-\rho^2}\,\omega_t$$

$$Z_t = \rho\left(\rho\left(\rho Z_{t-3} + \sqrt{1-\rho^2}\,\omega_{t-2}\right) + \sqrt{1-\rho^2}\,\omega_{t-1}\right) + \sqrt{1-\rho^2}\,\omega_t$$

…

$$Z_t = \rho^t Z_0 + \sqrt{1-\rho^2}\,\omega_t + \rho\sqrt{1-\rho^2}\,\omega_{t-1} + \rho^2\sqrt{1-\rho^2}\,\omega_{t-2} + \cdots + \rho^t\sqrt{1-\rho^2}\,\omega_0$$

Therefore, we have,

$$Z_t = \rho^t Z_0 + \sum_{i=0}^{t} \rho^i \sqrt{1-\rho^2}\,\omega_{t-i}$$

Since ω ~ i.i.d. (0,1),

$$Var(Z_t) = E\left[(Z_t - E(Z_t))^2\right] = E\left[\left(\sum_{i=0}^{t} \rho^i \sqrt{1-\rho^2}\,\omega_{t-i}\right)^2\right] = (1-\rho^2)\sum_{i=1}^{t} \rho^{2i}\omega_{t-1}^2$$
$$= (1-\rho^2)(\omega_t^2 + \rho^1\omega_{t-1}^2 + \rho^2\omega_{t-2}^2 + \cdots \rho^t\omega_0^2)$$

$$\lim_{t\to\infty} Var(Z_t) = (1-\rho^2)\frac{1}{1-\rho^2} = 1$$