Noise and expected return in Chinese A-share stock market

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ABSTRACT

Noise is defined as the deviation of a stock's current price from its fundamental value. According to recent studies, the noise not only influences stock returns significantly (Arnott, etc., 2007), but gives rise to firm size, book-to-market equity and momentum effects to some extent (Barber, etc., 2006, etc.). This paper seeks to determine whether a noise risk premium exists in the Chinese stock market after adjusting for market premium, firm size, book-to-market equity and momentum effects.

Our finding suggests that there is no obvious causal relation of noise to firm size effect, book-to-market equity effect and momentum effect respectively. However, noise itself can capture a portion of variations in stock returns which market premium, size, book-to-market equity and momentum factors cannot.

1. Introduction

The noise caused by the unpredictability of traders' beliefs (Barber, Odean & Zhu, 2006) is generally defined as deviations from equilibrium. Owing to this noise, stock price can diverge significantly from fundamental values (De Long, Shleifer, Summer & Waldman, 1990). Arnott, Hsu, Liu and Markowitz (2007) theoretically estimate a higher risk premium for stock with negative noise because the negative pricing error makes it to be undervalued, and vice versa. Hence, stocks with negative noise usually outperform stocks with positive noise, and it is reasonable to assume that noise has power in influencing the stock returns.

For value stocks (with high book-to-market equity ratio) which typically have had poor past performance, naïve investors (noise investors) might assume a trend in stock prices by ranging from extrapolating a past earnings decrease too far into the future, through to overreacting to good or bad news. When some of these poorly performing firms are turned around, investors are surprised and the stocks of these firms experience high returns (Lakonishok, Shleifer & Vishny, 1994). Hence, the high returns to value stocks (and the low returns to growth stocks) are due to the noise in stock prices which is caused by the systematically wrong expectation about the future of noise investors.

Barber, Odean and Zhu (2006) offer three reasons for the greater return spreads of small stocks. First, individual noise investors tend to tilt their investments toward small stocks. Second, the coordinated trading of individual investors is more likely to impact on small stocks. Third, the limits to arbitrage are greater for small stocks. Nevertheless, Arnott (2005a) illustrated the firm size effect created by the price noise. A stock with lower true fair value and positive pricing error will have a high price, with that it may have larger market capitalization. The largest cap stock is likely to be ranked at the top by capitalisation, at least partly because it has a positive noise term large enough to put the stock at the top. In short, the top-ranked stock is considerably more likely to have a positive than a negative pricing error (Arnott, 2005a). To the contrary, small cap stocks might be the result of high fair values with negative noise. Then, as more large cap stocks and more small cap stocks are creating than the true fair value would justify, the ‘large cap stocks’, which are the result of a positive noise, will have a lower return, and the ‘small cap stocks’, which are the result of a negative noise, will have a higher return (Arnott, 2005a). Hence, small stocks outperform large stocks, on average, over time.

Jordan (2006) suggests that the noise traders provide a crucial role in that price is not fully revealing and the mere existence of noise traders makes the joint existence of momentum and overreaction possible. His main contribution is that noise trading in markets, which can be rational and substantial, is sufficient for momentum and long-term reversals to occur in equilibrium. Hence, the effects of noise should be concerned, and the noise leads to a better understanding of why consumption patterns, where noise is comparatively low, are different from stock pricing patterns, where noise is quite high (Jordan, 2006).

According to Lakonishok, Shleifer and Vishnny (1994), Barber, Odean and Zhu (2006), Arnott (2005a), and Jordan (2006) noise could be a factor in explaining the firm size, book-to-market equity and momentum effects to some extent, as that it influences the stock returns significantly (Arnott, Hsu, Liu and Markowitz, 2007). In this context, an investigation that the significance of the noise effect in the presence of firm size, book-to-market equity and momentum factors needs to be done in order to determine the importance of noise in capturing the variation in stock returns.

This study compared the returns of portfolios with positive noise and negative noise to determine the noise effect. The positive access returns indicate that the negative noise portfolios outperform the positive noise portfolios, which is consistent with the argument of Arnott, Hsu, Liu and Markowitz (2007). Then, the noise factor was added to the Carhart's (1997) four factor model (contains market premium, size, book-to-market equity and momentum factors as independent varibles) as a new explanatory variable to test the existence of noise risk premium after adjusting for the Fama and French three factors and momentum factor. Evidence that the noise risk premium does exist after adjusting for market premium, size factor and book-to-market equity factor is observed from both time series regressions and panel regressions. However, the findings do not agree with the arguments of Lakonishok, Shleifer and Vishnny (1994), Barber, Odean and Zhu (2006), Arnott (2005a), and Jordan (2006) as our empirical results are against that noise creating the firm size effect and book-to-market equity effect and momentum effect.

The contributions of our work are as follows. First, the noise has been aware of its importance in influencing the stock returns (Arnott, Hsu, Liu & Markowitz, 2007), and probably, leads to size, book-to-market equity and momentum effects. However, to our knowledge, no empirical investigation has been done to test determine whether the noise risk premium exists after adjusting for market premium, firm size, book-to-market equity and momentum factors so far. Our study confirms the noise effect, however, casts doubts on the causal relation of noise to firm size, book-to-market equity and momentum effects respectively with empirical evidence. Second, panel regression model is introduced in asset pricing analysis as its significant efforts entered in our research. Although it is rarely utilised in this area before, its importance in empirical tests should not be ignored.

2. Data and Methodology

2.1 Data

According to Wang and Cheng (2004), the Chinese A-share stock market has two typical characteristics. First, short sales are strictly prohibited, which effectively limits the supply of tradable shares and thus has an effect on stock price formation. Second, the market is dominated by a large number of unsophisticated individual investors (noise traders). Most of these individual investors possess only a rudimentary knowledge of stock investments. Hence, with the lack of qualified security analysts and low transparency in the market, they behave like noise traders, selecting stocks based on past price trends and trading on rumors (Kang, Liu & Ni, 2002). This practice in China is known as 'stir-frying stocks': accompanied with limited effects of arbitrage against the noise trading, this accounts for the excessive speculation where stock prices are often pushed up several hundred percent and quickly corrected later (Kang, Liu & Ni, 2002). Consequently, noise in stock prices is significant.

Since reliable information on listed companies (especially, on small firms) in the Chinese stock market is not readily available, the stock prices are driven by rumors and investor sentiment, which can be easily manipulated by speculators (Kang, Liu & Ni, 2002). With the restriction of short selling, the speculators may find it easier to manipulate the sentiment on small stocks because of a relative lack of information. They may also find it more profitable to create bullish (rather than bearish) sentiment on small stocks since bullish stocks can attract all investors but bearish stocks concern only those who currently hold them. As a result, returns of small firms may lead those of large firms (Kang, Liu & Ni, 2002). For book-to-market equity effect, following the rumors and their own sentiment while without short selling to eliminate the mispricing, the overreactions of noise investors push the prices deviate from the fundamental values. Then high and low book-to-market equity ratios could be created temporarily due to they are under-priced and over-priced respectively. Hence, high book-to-market equity ratio stocks outperform low book-to-market equity ratio stocks. Wong, Tan and Liu (2006) show with strong statistical evidences that smaller firms and values stocks (with high book-to-market equity ratio) perform better in the Shanghai stock market. Besides, Kang, Liu & Ni (2002) find statistically significant abnormal profits for some short-horizon momentum strategies. Their analysis indicates that overreaction of individual traders (most of them are noise traders) to firm-specific information is the most important determinant of short-term contrarian profits. Therefore, the Chinese stock market might be a good sample for examining the noise effect and investigating its causal relation to size, book-to-market and momentum effects.

Monthly data on stocks in the Shanghai A-share and Shenzhen A-share indices covering the period from January 2000 to December 2007 were obtained from Datastream. To be included in the sample, a firm must have available information on capitalisation and relevant accounting data (P/E and P/B ratio etc.) to enable the analysis of firm size and an estimation of intrinsic value. The advantage of the data is that it contains most trading A-share stocks in both Shanghai and Shenzhen stock market which enables the noise effect to be captured completely and produce more convincing statistical evidence. Overall, in our sample, the stocks from Shanghai A-share index take approximately 60% while the other 40% of stocks are from Shenzhen A-share index. Following Drew, Naughton and Veeraraghavan (2003), market return is the capitalization of weighted returns on all stocks in the sample. For the risk free rates, the three months China time deposit rate is used.

2.2 Portfolio Aggregation Procedures

In this study, the mimicking portfolio approach of Fama and French (1993) is used in constructing portfolios on market capitalization and book-to-market equity. The sample stocks of each year are ranked according to their market capitalization at the beginning of the year and are divided into three groups of approximately an equal number of stocks. Group 1 contains the biggest stocks while group 3 contains the smallest. The difference between the returns of the biggest and smallest portfolios is represented by SMB which captures the risk factor in returns relating to firm size. The book-to-market equity is used to form the portfolios. The HML factor is estimated as the difference by subtracting the return of the portfolio with lowest book-to-market equity from the return of the portfolio with highest book-to-market equity. What differs in this study from what is usually done is that the stocks are further ranked independently by noise which is defined as the deviation between stock price and its fundamental value and sorted into triplet. The difference between returns of the portfolios with negative noise and those with positive noise is estimated the NMP factor. The excess returns over the risk free rate of those 27 portfolios are used as dependent variables to test the noise effect. Besides, for the momentum effect, the methodology of Jegadeesh and Titman (1993) is adopted. For the 27 portfolios, stocks are first sorted into 3 quintiles in descending order on the basis of their past returns. The “winner” is the first quintile portfolio containing stocks with highest returns and the “loser” is the bottom portfolio. The difference (WML) in returns between the winner portfolio and the loser portfolio is related to the return premium for the momentum strategy.

2.3 Noise estimation

This paper estimates the noise from two approaches: the P/B method and the P/E and P/B combined method.

The market prices can be obtained readily. Hence, the estimation of the fundamental value of the stocks is the key to measure the noise since it is defined as the deviation of price from the fundamental value. Two different approaches to firm valuation are by far the most commonly used: the discounted cash flow (DCF) method and relative valuation method (the multiple method). Recently, the relative valuation method has prevailed over the DCF method for the following reasons: based on the argument of Kaplan and Ruback (1995) that the discount factor is estimated from the CAPM, Yee (2008) argued that DCF analysis inevitably leads to an imprecise answer owning to the inherent shortcomings of CAPM (the estimation of beta and adopting a value for the elusive equity risk premium) and uncertainty in prospective cash flows (limited available information).

Chan and Chen (1991) and Ohlson (1988; 1995) consider the importance of P/B in valuation. Respectively, the P/B ratio reflects the production efficiency of a firm and the P/B ratio represents a firm’s excess rate of return caused by the firm’s superior performance. To the contrary, Cheng and McNamara (2000) found that the P/E benchmark valuation method performs better than the P/B benchmark valuation method, but that the P/E and P/B combination method outperforms either the P/E or the P/B individual method. Therefore, for the multiple approaches, it seems reasonable to choose both the P/B and the P/E and P/B combination method as they complement each other in estimating the fundamental valuation of stock.

As the key point of stock valuation methods, benchmark P/E multiples and benchmark P/B multiples are referred to as harmonic mean P/E and P/B respectively and are determined from a set of comparable firms (four in this study) of similar size, return on equity (ROE) and from the same industry as the target firm (Baker & Ruback, 1999, Cheng & McNamara, 2000, and Park & Lee, 2003). Baker and Ruback (1999) demonstrated that the magnitude of pricing errors tends to increase with price, as harmonic mean gives less weight to companies with relatively price-to-value driver ratios to minimize price-deflated pricing errors (Liu, Nissim & Thomas, 2007). It is a better estimator of the industry multiple than other estimators as the arithmetic mean or median (Baker and Ruback, 1999).

2.3.1 The P/B method

$$\overline{PB_{i,t}} = \frac{1}{1/n\sum_{n=j}^{n=1}(B_{j,t}/P_{j,t})},\ (j \neq i) \qquad (1); \qquad V_{i,t}^{P/B} = B_{i,t} * \overline{PB_{i,t}} \qquad (2)$$

Where $\overline{PB_{i,t}}$ is the benchmark P/B multiple (harmonic mean) for the target firm i at time t, $P_{j,t}$ is price per share of equity for firm j at the end of period t, $B_{j,t}$ is the book value per share for firm j at the end of period t. $V_{i,t}^{P/B}$ is the fundamental value per share of firm i, which is estimated by using P/B valuation method as equation (2).

2.3.2 The P/E and P/B combined method

Cheng and McNamara (2000) described the P/E and P/B combined valuation method as taking the simple average of valuations from the P/E and the P/B approaches.

$$\overline{PE_{i,t}} = \frac{1}{1/n\sum_{n=j}^{n=1}(E_{j,t}/P_{j,t})},\ (j \neq i) \qquad (3); \qquad V_{i,t}^{P/E} = E_{i,t} * \overline{PE_{i,t}} \qquad (4);$$

$$V_{i,t}^{P/E\&P/B} = \frac{(V_{i,t}^{P/E} + V_{i,t}^{P/B})}{2} \qquad (5)$$

$\overline{PE_{i,t}}$ is the benchmark P/E multiple (harmonic mean) for the target firm i at time t, $E_{j,t}$ is the annual earnings per share for firm j at the end of period t, $V_{i,t}^{P/E}$ is the fundamental value per share of firm i estimated from P/E approach at time t. $V_{i,t}^{P/E\&P/B}$ is the fundamental value per share of firm i estimated from the P/E and P/B combined approach at time t, which is the average of $V_{i,t}^{P/B}$ and $V_{i,t}^{P/E}$. The others variables are defined in equation (1) and (2).

According to the noise measurement equation (Black, 1986), once the fundamental value is achieved from the P/B and the P/E and P/B combined methods, we can estimate the value of noise by subtracting the fundamental value from the price as follows:

$$l_{i,t} = P_{i,t} - V_{i,t} \qquad (6)$$

Where $l_{i,t}$ is the noise of stock i at time t, which is the difference of the price $P_{i,t}$ and the fundamental value $V_{i,t}$.

2.4 Testing models

2.4.1 Time series regression model

For the empirical tests, firstly, the sensitivity of excess returns to noise factor (NMP) alone is examined according to the simple linear regression model below:

$$R_{i,t} - R_f = a_i + n_i NMP_t + e_{i,t} \qquad (7)$$

Where $R_{i,t}$ is the excess return of portfolio i at time t, R_f is the risk free rate, the noise factor NMP_t is the excess average return of portfolio with negative noise stocks over portfolio with positive noise firm stocks at time t, and $e_{i,t}$ is the idiosyncratic error term at time t.

Then, the excess returns of each portfolio are regressed on their corresponding variables of market premium, SMB, HML, WML and NMP, to test whether the noise risk premium exists after controlling for market premium, size, book-to-market equity and momentum factor. The testing model is shown as follows:

$$R_{i,t} - R_f = a_i + b_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + w_i WML_t + n_i NMP_t + e_{i,t} \quad (8)$$

Where R_m is the market return, SMB_t is the excess average return of portfolio with small firm stocks over portfolio with large firm stocks at time t, HML_t is the excess average return of a portfolio with high book-to-market equity stocks over the portfolio with low book-to-market ratio equity stocks at time t, and WML_t is the excess average return of a portfolio with "winner" stocks over the portfolio with "loser" stocks at time t. The other variables are defined in equation (7).

2.4.2 Panel regression model

Besides using the time series regression model, what differs in this study are from that the cross-sectional and time series features of the data set are combined to run the panel regression. To estimate both time series consistent effects caused by the portfolio feature and cross-sectional fixed effects due to the missing value in several months in our sample is the motivation for us to utilise the panel regression analysis.

For dealing with the panel regression, it is common in applied work to find a variable a_i in equation (9) referred to as a fixed effect which captures all unobserved, time-constant factors that affect the dependent variable (Wooldridge, 2006). The other variables are defined in equation (7) and (8).

$$R_{i,t} - R_f = a_{i,t} + b_{i,t}(R_m - R_f) + s_{i,t}SMB + h_{i,t}HML + w_{i,t}WML + n_{i,t}NMP + a_i + e_{i,t} \qquad (9)$$

Hence, the model shown above is named an unobserved effects model. In applied works, such models are usually estimated by fixed effect estimator or random effect estimator. According to the results of the Hausman tests which are presented in Table 4, the fixed effects estimator is preferred because the random effects estimator will provide an inconsistent and biased estimation in that situation.

According to Wooldridge (2006), a traditional view of the fixed effects model is to assume that the unobserved effect a_i is a parameter to be estimated for each ***i***. Hence, in the testing model, a_i is the intercept for each portfolio or month. The way to estimate an intercept for each ***i*** is to put dummy variables for each cross-sectional observation and time period, along with the explanatory variables (Wooldridge, 2006). Therefore, the fixed effects estimator can be achieved by utilising the dummy variable regression.

Dummy variables added for each month and portfolio to obtain the fixed effects estimates, provides the following equation:

$$R_{i,t} - R_{f,t} = a_{i,t} + b_{i,t}(R_{m,t} - R_{f,t}) + s_{i,t}SMB + h_{i,t}HML + w_{i,t}WML + n_{i,t}NMP + g_t d_t + q_i d_i + e_{i,t} \qquad (10)$$

t = March, April, June …, December; i = Portfolio 111, 112 …, 333

3. Empirical analysis

3.1 Summary statistics

Table 1 presents the summary statistics are reported in terms of monthly returns, means, standard deviations, test-statistics and P-value of Jarque-Bera tests, and number of observations. In addition to the usual summary statistics, this table presents the 'average noise' of each portfolio examined using the methods introduced above.

Consistent with what Fama and French's (1993) finding in the U.S.A. stock market, small size stocks outperform the large size stocks no matter the market is up or down. However, the unusual phenomenon of low book-to-market equity stocks generating returns in excess of stocks with a high book-to-market equity ratio casts doubt on the traditional theories which show a preference of high book-to-market stock. Although this finding looks strange and interesting, it is consistent with that of Drew, Naughton and Veeraraghavan (2003) who use the Shanghai A-share stocks as their sample.

By controlling size and book-to-market equity ratio, the much better performance of negative noise portfolios over positive noise portfolios strongly supports Arnott, Hsu, Liu and Markowitz's (2007) theoretical analysis. According to Arnott (2005a), a lot of large size stocks are created by positive noise which is high enough to push the capitalization to the top. And Lakonishok, Shleifer and Vishny (1994) suggest that high book-to-market equity ratio of stocks is due to the over-buying behaviour of noise investors that drives price much higher than the fundamental value. However, those arguments are not supported in the Chinese stock market, since neither large size stock nor high book-to-market equity stocks tend to have higher positive noise. Therefore, it is reasonable that the noise might not create firm size effect or book to market effect, as that firm size, book-to-market equity and noise affect stock returns independently.

The null hypothesis of the Jarque-Bera normality test cannot be rejected in 5 percent significance level for most portfolios, which indicates that most of those returns follow the normal distribution. This is important because ignoring other possible problems, it implies the usual t-tests and F-tests for empirical regression testing are valid.

3.1 The time series regression analysis

Table 2, 3 and 4 show the time series regression results. Most of the intercepts are insignificant and only a few of them have positive signs, which indicate that most portfolios do not generate positive abnormal returns controlling for the explanatory fundamental factors. Confirming the findings of Markowitz (1952), Sharpe (1964), Lintner (1965), and Fama and French (1993), market premium shows its importance in affecting the stock returns as the coefficients for market premium are significant for all regressions.

As Fama and French (1995) argued, besides the excess market returns and other factors, size is important in distinguishing the returns variation of small and large capitalization stock portfolios. All small stock portfolios have positive risk premium for the proxy of size factor (SMB) while large stock portfolios would generate lower returns due to the negative slopes of SMB. The regressions present a book-to-market equity effect in portfolio returns. Control by the capitalization and noise, the coefficients on book-to-market equity factor (HML) increase substantially from low book-to-market equity portfolios to high book-to-market equity portfolios. However, the negative high book-to-market equity portfolios excess returns combined with the positive slopes of HML for high book-to-market equity portfolios generate a negative risk premium. That is consistent with this study’s finding that low book-to-market equity portfolios generate returns in excess of high book-to-market equity portfolios in the statistical summary section, but this challenges the argument of Fama and French (1993, 1995). Drew, Naughton and Veeraraghavan (2003) have similar findings in the Shanghai stock market and provide two possible reasons in explaining that. Firstly, the well-recognized problems of accounting standards in China may cause concern about the book values. Secondly, the unusual behaviour of the HML factor may lie somewhere in cross-sectional differences in the levels of non-traded state and institutional holdings. All those arguments suggest that in the Chinese stock market, the book-to-market equity effect is not as pervasive as previous findings in the U.S.A. stock market. Besides, for more than half regressions, the coefficients of WML tend to be significant, hence, the momentum effect is also observed in the Chinese stock market.

The noise effect is determined since the noise factor shows its importance in explaining the variation in portfolio returns no matter the size, book-to-market equity and momentum factors are controlled or not. For positive noise portfolios and negative noise portfolios, a sign difference exists between the coefficients of NMP. That is due to a negative trade off presented between the returns and the noise. For an investor holding a negative noise portfolio, the expected return premium has to be higher to compensate for an additional downside risk in stock prices. Negative noise portfolios have higher noise risk premium to promote the overall performance, while positive noise portfolios generate lower returns because of the lower noise risk premium. As that, portfolios with positive noise have negative slope for NMP while the coefficients of NMP for negative noise portfolios enter positively. However, the causal relation of noise to size, book-to-market equity and momentum effects respectively can't be supported as noise risk premium does not enter special positive efforts for either small size or low book-to-market equity portfolios, and no obvious correlation is observed between the slops of WML and NMP.

3.3 The panel regressions analysis

According to the panel regressions results shown in Table 6, extreme insignificant coefficients indicate that cross-sectional portfolio dummies don’t contribute important effect to the portfolio access returns. Hence, there is no reason to keep portfolio dummy variables in our model.

For both size, book-to-market equity and P/B noise formed portfolios and size, book-to-market equity and P/E & P/B noise formed portfolios, estimates above are roughly consistent with each other in terms of sign, value and significance level.

Market premium enter significant positive effects on portfolio excess returns. The size factor is crucial in explaining the returns variation of portfolios as its coefficient is positive and statistically significant. And it could be confirmed that small stocks take main position overall because the portfolio returns tend to have positive correlation with small size excess returns which represent the size factor. Book-to-market equity and momentum factors enter negative effect in influencing the portfolio returns. Incorporating the special low book-to-market equity and loser effects in Chinese stock market, that high book-to-market equity and past winner stocks have an important impact toward the performance of the portfolios is determined.

Nevertheless, the negative trade off between noise and stock returns is supported again by the panel regression results. Since the parameter shows the importance of noise factor in affecting the portfolio access returns with high t-statistics and low P-value, it is concluded that the noise captures different element of risk that other control factor can’t explain. Besides, as the portfolio returns have the same moving trend with negative noise portfolio excess returns (NMP), it is obvious that compared with positive noise stocks, there are more negative noise stocks exist in Chinese stock market during our sample period.

The coefficients for the monthly dummy are around 0.025 and are both individually and jointly significant, which indicates that compared with January, February and May, the portfolio returns are higher in the remaining months. Actually, that is due to the missing data in those three months.

Heteroskedastic and slightly autocorrelated residuals for the models were observed after utilising the one way fixed effect estimator. By comparing the results of pure fixed effects regressions and period weighted regressions, that the problem exists cross-sectionally was determined. Hence, additionally, models for using a variant of weighted GLS (cross-section SUR) which corrects both cross-section heteroskedasticity and contemporaneous correlation (Eviews 5 User's guide, 2004) are also estimated in this study. Comparing the weighted statistics and unweighted statistics, shows that the models are improved after utilising weighted GLS (cross-section SUR) since the adjusted R-squared increases and the Durbin-Watson statistics is modified. Overall, the results of the one-way fixed effects GLS panel regressions do support that the noise risk premium exists in the Chinese stock market even adjusting for market premium, Fama and French three factors, and momentum effect.

4. Conclusion

Our empirical testing results confirm the existence of noise risk premium after adjusting for market effect, size, book-to-market equity and momentum factors in the Chinese stock market. Arnott, Hsu, Liu and Markowitz (2007) theoretically estimate a higher risk premium for stock with negative noise because the negative pricing error makes it to be undervalued, and vice versa. Hence, stocks with negative noise usually outperform stocks with positive noise. This argument is supported since the basic summary shows the positive access returns of negative noise portfolios even size and book-to-market equity have been controlled and coefficients of noise factor NMP are significant in both time series and panel regressions.

However, we don't achieve evidence to justify the causal relation of noise to firm size effect, book-to-market equity effect, and momentum effect respectively. According to Lakonishok, Shleifer and Vishnny (1994), Barber, Odean and Zhu (2006), Arnott (2005a), and Jordan (2006), the noise not only creates the higher returns for small size and high book-to-market equity stocks to some extent, but also plays a crucial role in understanding the momentum effect. Doubts on those claims arose in this study because neither small size nor low book-to-market equity stock tend to have negative or even lower noise compared with large size and high book-to-market equity stock, and neither SMB, HML nor WML can be substituted by NMP in regressions. Therefore, it is reasonable that size factor, book-to-market equity factor, momentum factor and noise influence the stock returns independently.

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Table 1. Summary statistics of 27 portfolios formed by size, BTMV and P/B noise and another 27 portfolios sorted by size, BTMV and P/E & P/B noise: January 2000 to December 2007.

				Size, BTMV and P/B noise sorted portfolios						Size, BTMV and P/E & P/B noise sorted portfolios					
						Normality test						Normality test			
Size	**BTMV**	**Noise**	**Portfolio**	**Mean**	**Std. Dev.**	**Jarque-Bera**	**Prob.**	**Observations**	**Average Noise**	**Mean**	**Std. Dev.**	**Jarque-Bera**	**Prob.**	**Observations**	**Average Noise**
Small	**Low**	**Negative**	**P111**	-0.013	0.102	2.380	0.304	68	-0.639	-0.012	0.099	2.186	0.335	68	-0.088
		Mixed	**P112**	-0.017	0.100	1.960	0.375	68	4.403	-0.018	0.099	2.180	0.336	68	4.321
		Positive	**P113**	-0.016	0.089	4.368	0.113	68	9.050	-0.016	0.091	4.385	0.112	68	8.435
	Mid	**Negative**	**P121**	-0.014	0.102	2.194	0.334	68	-1.531	-0.012	0.101	1.823	0.402	68	-1.789
		Mixed	**P122**	-0.014	0.098	0.827	0.661	68	2.432	-0.015	0.099	1.310	0.519	68	2.506
		Positive	**P123**	-0.017	0.093	2.178	0.337	68	20.708	-0.018	0.094	2.410	0.300	68	18.236
	High	**Negative**	**P131**	-0.016	0.104	2.262	0.323	68	-3.930	-0.017	0.097	2.012	0.366	68	-3.640
		Mixed	**P132**	-0.018	0.095	2.651	0.266	68	0.978	-0.021	0.105	2.254	0.324	68	1.097
		Positive	**P133**	-0.028	0.094	9.155	0.010	68	5.361	-0.026	0.092	5.011	0.082	68	5.077
Mid	**Low**	**Negative**	**P211**	-0.009	0.088	2.089	0.352	68	0.176	-0.011	0.087	3.366	0.186	68	0.046
		Mixed	**P212**	-0.009	0.090	2.483	0.289	68	5.176	-0.007	0.090	2.087	0.352	68	5.092
		Positive	**P213**	-0.013	0.083	9.799	0.007	68	11.560	-0.012	0.084	9.818	0.007	68	11.213
	Mid	**Negative**	**P221**	-0.010	0.095	2.321	0.313	68	-1.425	-0.008	0.092	1.129	0.569	68	-1.682
		Mixed	**P222**	-0.013	0.093	2.110	0.348	68	2.489	-0.014	0.093	2.310	0.315	68	2.410
		Positive	**P223**	-0.021	0.084	1.383	0.501	68	7.353	-0.021	0.086	1.541	0.463	68	6.915
	High	**Negative**	**P231**	-0.014	0.094	1.739	0.419	68	-3.580	-0.013	0.093	2.102	0.350	68	-3.233
		Mixed	**P232**	-0.019	0.097	5.443	0.066	68	0.749	-0.019	0.095	2.170	0.338	68	0.856
		Positive	**P233**	-0.020	0.094	1.706	0.426	68	4.497	-0.020	0.095	2.691	0.260	68	4.257
Big	**Low**	**Negative**	**P311**	-0.006	0.081	7.525	0.023	68	-5.261	-0.003	0.078	6.385	0.041	68	-1.820
		Mixed	**P312**	-0.005	0.075	2.806	0.246	68	6.455	-0.009	0.076	1.164	0.559	68	6.750
		Positive	**P313**	-0.018	0.084	20.712	0.000	68	16.650	-0.019	0.087	25.697	0.000	68	16.823
	Mid	**Negative**	**P321**	-0.013	0.074	6.761	0.034	68	-2.012	-0.014	0.076	7.164	0.028	68	-2.375
		Mixed	**P322**	-0.015	0.088	1.243	0.537	68	3.308	-0.015	0.078	1.659	0.436	68	3.306
		Positive	**P323**	-0.023	0.087	2.112	0.348	68	9.418	-0.023	0.091	2.038	0.361	68	9.121
	High	**Negative**	**P331**	-0.017	0.080	5.322	0.070	68	-4.240	-0.020	0.084	5.030	0.081	68	-4.149
		Mixed	**P332**	-0.022	0.088	1.083	0.582	68	0.721	-0.021	0.084	1.819	0.403	68	0.678
		Positive	**P333**	-0.022	0.080	0.347	0.841	68	5.669	-0.022	0.079	1.270	0.530	68	5.085
			Market	-0.017	0.075	0.583	0.747	68		-0.017	0.075	0.583	0.747	68	

Table 2. Time series regression results for 27 portfolios formed by size, BTMV and P/B noise and another 27 portfolios sorted by size, BTMV and P/E & P/B noise: January 2000 to December 2007

The one factor model: $R_{i,t} - R_f = a_i + n_i NMP_t + e_{i,t}$

				portfolios formed by size, BTMV and P/B noise				portfolios formed by size, BTMV and P/E&P/B noise			
Size	**BTMV**	**Noise**	**Portfolio**	**Constant**	**NMP**	**Adj. R-sq.**	**DWTS**	**Constant**	**NMP**	**Adj. R-sq.**	**DWTS**
Small	**Low**	**Negative**	**P111**	-0.017	1.286	0.235	1.806	-0.017	1.035	0.109	1.450
				(-1.539)	(4.646)***			(-1.488)	(3.038)***		
		Mixed	**P112**	-0.019	0.948	0.126	1.844	-0.018	0.754	0.053	1.584
				(-1.682)*	(3.262)***			(-1.526)	(2.185)**		
		Positive	**P113**	-0.017	0.286	0.001	1.801	-0.016	0.118	-0.013	1.702
				(-1.539)	-1.032			(-1.499)	-0.371		
	Mid	**Negative**	**P121**	-0.017	1.190	0.169	0.102	-0.018	0.964	0.090	1.735
				(-1.511)	(3.826)***			(-1.423)	(2.768)***		
		Mixed	**P122**	-0.016	0.974	0.121	1.752	-0.018	0.766	0.069	1.632
				(-1.478)	(3.196)***			(-1.555)	(2.439)**		
		Positive	**P123**	-0.017	0.190	-0.009	1.688	-0.018	-0.215	-0.007	1.613
				(-1.511)	-0.611			(-1.668)	(-0.739)		
	High	**Negative**	**P131**	-0.032	1.253	0.191	1.542	-0.023	0.321	0.001	1.598
				(-2.638)**	(4.097)***			(-2.145)**	(1.029)		
		Mixed	**P132**	-0.030	0.942	0.124	1.423	-0.022	0.370	0.001	1.413
				(-2.653)***	(3.240)***			(-1.818)	(1.040)		
		Positive	**P133**	-0.032	0.253	-0.005	1.542	-0.028	-0.074	-0.014	1.466
				(-2.638)**	-0.828			(-2.351)**	(-0.21)		
Mid	**Low**	**Negative**	**P211**	-0.013	0.891	0.110	1.507	-0.010	0.772	0.075	1.588
				(-1.272)	(3.052)***			(-0.94)	(1.894)*		
		Mixed	**P212**	-0.011	0.451	0.016	1.694	-0.009	0.356	0.004	1.732
				(-0.985)	-1.445			(-0.836)	(0.828)		
		Positive	**P213**	-0.013	-0.109	-0.013	1.507	-0.013	-0.100	-0.013	1.500
				(-1.272)	(-0.371)			(-1.325)	(-0.336)		
	Mid	**Negative**	**P221**	-0.022	1.100	0.219	1.539	-0.020	0.834	0.097	1.430
				(-2.050)**	(4.447)***			(-1.779)*	(2.869)***		
		Mixed	**P222**	-0.022	0.870	0.141	1.515	-0.020	0.583	0.043	1.421
				(-2.059)**	(3.457)***			(-1.755)*	(2.007)**		
		Positive	**P223**	-0.022	0.100	-0.013	1.539	-0.019	-0.117	-0.012	1.530
				(-2.050)**	-0.404			(-1.766)*	(-0.433)		
	High	**Negative**	**P231**	-0.017	0.510	0.040	1.546	-0.016	0.304	0.002	1.562
				(-1.511)	-1.488			(-1.376)	(1.063)		
		Mixed	**P232**	-0.020	0.180	-0.009	1.381	-0.019	0.003	-0.015	1.404
				(-1.669)	-0.653			(-1.597)	(0.007)		
		Positive	**P233**	-0.017	-0.490	0.036	1.546	-0.016	-0.672	0.069	1.589
				(-1.502)	(-1.876)*			(-1.39)	(-2.439)**		

Big	**Low**	**Negative**	**P311**	-0.010	0.365	0.032	1.891	-0.008	0.111	-0.010	2.029
				(-1.067)	(1.787)*			(-0.8)	(0.556)		
		Mixed	**P312**	-0.004	-0.162	-0.004	1.495	-0.002	-0.218	0.006	1.531
				(-0.383)	(-0.839)			(-0.201)	(-1.184)		
		Positive	**P313**	-0.011	-0.635	0.115	1.891	-0.006	-0.755	0.184	1.880
				(-1.067)	(-3.112)***			(-0.576)	(-4.013)***		
	Mid	**Negative**	**P321**	-0.015	0.172	0.003	2.058	-0.014	0.007	-0.015	2.027
				(-1.662)	-1.087			(-1.475)	(0.041)		
		Mixed	**P322**	-0.011	-0.356	0.039	2.314	-0.012	-0.314	0.023	2.320
				(-1.089)	(-1.782)*			(-1.129)	(-1.608)		
		Positive	**P323**	-0.015	-0.828	0.281	2.058	-0.016	-0.904	0.073	2.196
				(-1.662)	(-5.220)***			(-1.752)	(-5.577)***		
	High	**Negative**	**P331**	-0.019	0.497	0.063	1.422	-0.019	-0.023	-0.009	1.351
				(-2.061)**	(2.339)**			(-2.066)**	(-2.132)**		
		Mixed	**P332**	-0.022	-0.100	-0.013	1.404	-0.023	0.168	-0.009	1.351
				(-2.039)**	(-0.414)			(-2.132)**	(0.619)		
		Positive	**P333**	-0.019	-0.503	0.064	1.422	-0.022	-0.126	-0.011	1.371
				(-2.061)	(-2.37)			(-2.213)**	(-0.612)		

(*the t-statistics is significant at 10% level, **the t-statistics is significant at 5% level, ***the t-statistics is significant at 1%level)

Table 3. Time series regression results for 27 portfolios formed by size, BTMV and P/B noise: January 2000 to December 2007

The five factor model:

$$R_{i,t} - R_f = a_i + b_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + w_i WML_t + n_i NMP_t + e_{i,t}$$

		Constant			NMP		
		Small	**Mid**	**Big**	**Small**	**Mid**	**Big**
Low	**Negative**	0.009	0.008	-0.002	0.188	0.203	0.396
		(1.856)*	(1.705)*	(-0.703)	(1.229)	(1.511)	(6.082)***
	Mid	0.006	0.012	0.011	0.248	-0.186	-0.253
		(2.010)**	(3.429)***	(1.779)*	(2.217)**	(-1.329)	(-1.771)*
	Positive	-0.010	0.001	-0.001	0.257	-0.208	-0.334
		(-2.16)**	(0.180)	(-0.166)	(1.100)	(-1.488)	(-3.599)***
Mid	**Negative**	0.003	0.002	-0.001	0.139	0.377	0.369
		(0.990)	(0.584)	(-0.683)	(0.817)	(3.810)***	(10.987)***
	Mid	0.002	0.002	0.003	0.020	0.206	-0.056
		(0.910)	(0.393)	(1.071)	(0.157)	(1.303)	(-0.546)
	Positive	-0.004	-0.002	-0.002	0.013	-0.521	(-0.380)
		(-1.254)	(-0.389)	(-0.788)	(0.124)	(-2.624)**	-9.018***
High	**Negative**	-0.008	-0.002	0.005	0.546	0.574	(0.246)
		(-1.752)	(-0.568)	(3.153)***	(2.264)**	(3.830)***	4.588***
	Mid	-0.013	0.001	0.008	0.542	0.542	(-0.172)
		(-2.561)**	(0.146)	(1.607)	(2.001)**	(2.226)**	-2.087**
	Positive	-0.008	0.004	(-0.005)	0.285	-0.229	(-0.302)
		(-1.702)*	(0.883)	(-1.345)	(2.235)**	(-1.846)*	(-3.496)***

		Mr-Rf			SMB		
		Small	**Mid**	**Big**	**Small**	**Mid**	**Big**
Low	**Negative**	0.970	0.985	0.885	0.683	0.339	-0.178
		(9.115)***	(16.428)***	(29.610)***	(9.115)***	(3.778)***	(-5.726)***
	Mid	0.918	0.986	0.910	0.866	0.638	0.082
		(15.019)***	(16.942)***	(17.014)***	(10.816)***	(5.129)***	(0.764)
	Positive	0.965	1.092	0.926	0.449	0.280	-0.119
		(15.169)***	(21.541)***	(18.807)***	(5.629)***	(4.391)***	(-1.793)*
Mid	**Negative**	0.922	0.920	0.986	0.673	0.485	-0.126
		(16.287)***	(21.629)***	(33.140)***	(7.091)***	(12.339)***	(-3.129)***
	Mid	1.053	1.053	1.026	0.644	0.443	-0.329
		(25.551)***	(22.817)***	(26.382)***	(13.148)***	(6.846)***	(-7.253)***
	Positive	1.085	1.050	1.002	0.619	0.444	-0.226
		(22.442)***	(14.008)***	(35.448)***	(10.311)***	(5.127)***	(-6.435)***
High	**Negative**	0.922	1.054	1.057	0.718	0.418	-0.155
		(12.169)***	(26.656)***	(38.621)***	(7.278)***	(5.735)***	(-3.067)***
	Mid	0.945	1.073	0.905	0.661	0.280	-0.095
		(14.326)***	(13.749)***	(14.709)***	(6.611)***	(2.736)***	(-1.287)
	Positive	0.929	0.994	0.927	0.687	0.431	-0.154
		(16.174)***	(14.622)***	(19.487)***	(9.027)***	(5.529)***	(-2.227)**

		HML			WML		
		Small	**Mid**	**Big**	**Small**	**Mid**	**Big**
Low	**Negative**	-0.236	-0.351	-0.317	0.190	0.053	-0.003
		(-1.420)	(0.010)**	(-6.385)***	(1.843)*	(0.498)	(-0.099)
	Mid	-0.594	-0.407	-0.148	-0.112	0.071	0.023
		(-5.274)***	(-3.223)***	(-1.118)	(-1.414)**	(0.913)	(0.433)
	Positive	-0.667	-0.697	-0.487	0.140	-0.046	0.034
		(-3.320)***	(-5.438)***	(-6.029)***	(2.696)***	(-0.954)	(0.585)
Mid	**Negative**	-0.008	-0.001	-0.033	0.094	0.088	-0.074
		(-0.092)	(-0.008)	(-1.029)	(1.099)	(1.920)*	(-1.961)**
	Mid	0.026	-0.053	0.002	-0.138	-0.186	-0.050
		(0.323)	(-0.429)	(0.023)	(-1.941)*	(-2.543)**	(-0.783)
	Positive	-0.028	-0.173	-0.028	0.091	-0.041	0.021
		(-0.255)	(-1.015)	(-0.846)	(0.992)	(-0.489)	(0.641)
High	**Negative**	-0.006	0.442	0.251	-0.151	-0.303	-0.111
		(-0.032)	(3.595)***	(4.698)***	(-1.030)	(-1.806)*	(-3.452)***
	Mid	-0.167	0.542	0.832	-0.114	0.165	0.043
		(-0.764)	(2.887)***	(4.952)***	(-0.670)	(0.940)	(0.547)
	Positive	0.292	0.381	0.219	-0.137	0.195	0.107
		(2.420)**	(2.501)**	(3.667)***	(-1.893)*	(1.491)	(1.705)*

Table 4. Time series regression results for 27 portfolios formed by size, BTMV and P/E & P/B noise: January 2000 to December 2007

The five factor model:

$$R_{i,t} - R_f = a_i + b_i(R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + w_i WML_t + n_i NMP_t + e_{i,t}$$

		Constant			NMP		
		Small	**Mid**	**Big**	**Small**	**Mid**	**Big**
Low	**Negative**	0.011	0.011	0.008	-0.183	0.074	0.027
		(2.175)**	(2.461)**	(1.921)*	(-1.156)	(0.385)	(0.364)
	Mid	0.007	0.010	0.012	0.298	-0.327	-0.223
		(1.457)	(2.539)***	(2.244)**	(2.182)**	(-2.013)**	(-1.811)*
	Positive	-0.005	-0.001	0.003	0.016	-0.312	-0.466
		(-0.958)	(-0.189)	(0.612)	(0.091)	(-2.231)**	(-2.433)**
Mid	**Negative**	0.004	0.003	-0.001	-0.325	0.186	0.216
		(0.870)	(0.970)	(-0.314)	(-0.872)	(2.224)**	(2.534)**
	Mid	0.000	0.000	0.001	0.232	0.155	0.146
		(0.047)	(0.067)	(0.368)	(1.087)*	(1.132)	(1.020)
	Positive	-0.004	0.001	-0.002	-0.260	-0.607	-0.463
		(-0.599)	(0.216)	(-1.229)	(-1.511)	(-4.816)***	(-13.158)***
High	**Negative**	-0.005	0.001	0.000	0.268	0.447	0.360
		(-1.215)	(0.369)	(0.199)	(1.405)	(1.818)*	(2.984)**
	Mid	-0.006	0.000	0.005	0.267	0.458	-0.351
		(-1.161)	(0.023)	(0.863)	(1.661)	(2.057)**	(-2.086)**
	Positive	-0.008	0.001	-0.005	-0.102	-0.045	-0.362
		(-1.634)	(0.308)	(-1.403)	(-0.599)	(-0.247)	(-3.106)***

		Mr-Rf			SMB		
		Small	**Mid**	**Big**	**Small**	**Mid**	**Big**
Low	**Negative**	0.979	0.975	1.118	0.785	0.424	-0.228
		(15.060)***	(13.915)***	(20.642)***	(10.592)***	(4.022)***	(-4.626)***
	Mid	0.868	1.006	0.903	0.894	0.596	0.087
		(13.164)***	(17.066)***	(17.311)***	(11.295)***	(4.896)***	(0.988)
	Positive	0.976	1.132	0.883	0.406	0.309	-0.048
		(14.154)***	(22.780)***	(16.368)***	(5.795)***	(4.293)***	(-0.572)
Mid	**Negative**	1.095	0.954	0.985	0.676	0.509	-0.009
		(11.612)***	(31.329)***	(24.677)***	(5.061)***	(12.806)***	(-0.198)
	Mid	0.979	0.982	1.110	0.785	0.522	-0.391
		(16.282)***	(13.728)***	(19.441)***	(11.526)***	(6.493)***	(-5.128)***
	Positive	0.879	1.071	0.963	-0.289	0.435	-0.265
		(10.600)***	(15.003)***	(39.056)***	(-2.855)***	(4.434)***	(-9.192)***
High	**Negative**	1.030	1.070	1.015	-0.331	0.429	-0.140
		(19.501)***	(27.393)***	(25.718)***	(-4.348)***	(5.898)***	(-1.680)
	Mid	0.885	1.046	0.964	0.761	0.406	-0.013
		(12.447)***	(12.090)***	(15.878)***	(8.719)***	(3.494)***	(-0.141)
	Positive	0.988	1.042	0.997	0.634	0.331	-0.236
		(14.430)***	(12.281)***	(20.156)***	(6.541)***	(3.895)***	(-3.196)***

		HML			WML		
		Small	**Mid**	**Big**	**Small**	**Mid**	**Big**
Low	**Negative**	-0.338	-0.365	-0.394	0.144	0.019	-0.169
		(-2.092)**	(-2.709)***	(-4.922)***	(1.418)	(0.276)	(-1.957)
	Mid	-0.155	-0.341	-0.140	0.155	0.144	0.055
		(-1.162)	(-2.621)**	(-1.257)	(1.731)*	(2.130)**	(0.944)
	Positive	-0.496	-0.698	-0.409	-0.081	-0.048	0.016
		(-2.742)***	(-4.400)***	(-4.299)***	(-0.876)	(-0.700)	(0.311)
Mid	**Negative**	-0.232	0.079	-0.038	-0.139	0.070	-0.227
		(-0.951)	(1.115)	(-0.707)	(-0.883)	(0.974)	(-4.525)***
	Mid	-0.006	-0.012	-0.148	-0.047	0.070	0.082
		(-0.072)	(-0.067)	(-1.816)*	(-0.447)	(0.675)	(1.077)
	Positive	-0.028	-0.246	0.032	0.517	-0.007	0.024
		(-0.141)	(-1.432)	(1.065)	(4.275)***	(-0.080)	(0.886)
High	**Negative**	-0.270	0.465	0.175	-0.222	0.050	-0.043
		(-1.138)	(2.096)**	(2.641)**	(-1.409)	(0.325)	(-0.872)
	Mid	0.051	0.382	0.835	-0.260	0.136	0.018
		(0.334)	(1.945)*	(4.473)***	(-2.656)***	(0.763)	(0.211)
	Positive	0.065	0.236	0.206	-0.117	0.034	0.081
		(0.403)	(1.391)	(2.673)**	(-1.302)	(0.346)	(0.721)

Table 5. The results of the Hausman fixed effect tests

Correlated Random Effects - Hausman Test				**Correlated Random Effects - Hausman Test**			
Test period random effects				**Test period random effects**			
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	**Prob.**	Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	**Prob.**
	279.674	4.000	**0.000**		247.003	4.000	**0.000**

Table 6. The panel regression results for 27 portfolios formed by size, BTMV and P/B noise and another 27 portfolios sorted by size, BTMV and P/E & P/B noise: January 2000 to December 2007

Panel regression model:

$$R_{i,t} - R_{f,t} = a_{i,t} + b_{i,t}(R_{m,t} - R_{f,t}) + s_{i,t}SMB + h_{i,t}HML + w_{i,t}WML + n_{i,t}NMP + g_t d_t + e_{i,t}$$

Dependent Variable: The excess returns of portfolios formed by size, BTMV and P/B noise					**Dependent Variable: The excess returns of portfolios formed by size, BTMV and P/E&P/B noise**				
Method: Panel EGLS (Cross-section SUR)					**Method: Panel EGLS (Cross-section SUR)**				
Variable	**Coefficient**	**Std. Error**	**t-Stat**	**Prob.**	**Variable**	**Coefficient**	**Std. Error**	**t-Stat**	**Prob.**
C	-0.023	0.004	-5.762	0.000	**C**	-0.023	0.004	-5.627	0.000
Mr-Rf	0.96	0.013	72.516	0.000	**Mr-Rf**	0.968	0.014	69.053	0.000
SMB	0.246	0.008	29.002	0.000	**SMB**	0.306	0.009	34.238	0.000
HML	-0.042	0.013	-3.366	0.001	**HML**	-0.049	0.013	-3.879	0.000
WML	-0.069	0.007	-10.035	0.000	**WML**	-0.083	0.007	-12.048	0.000
NMP	0.151	0.012	12.304	0.000	**NMP**	0.037	0.012	3.11	0.002
March	0.018	0.005	3.573	0.000	**March**	0.018	0.005	3.509	0.001
April	0.022	0.005	4.569	0.000	**April**	0.024	0.005	4.646	0.000
June	0.021	0.005	4.232	0.000	**June**	0.025	0.005	5.006	0.000
July	0.023	0.005	4.766	0.000	**July**	0.025	0.005	4.944	0.000
August	0.025	0.005	5.124	0.000	**August**	0.026	0.005	5.143	0.000
September	0.022	0.005	4.627	0.000	**September**	0.021	0.005	4.184	0.000
November	0.038	0.005	7.691	0.000	**November**	0.034	0.005	6.633	0.000
December	0.022	0.005	4.614	0.000	**December**	0.023	0.005	4.594	0.000

Weighted Statistics				**Weighted Statistics**			
R-squared	0.792	**Adjusted R-squared**	0.790	**R-squared**	0.805	**Adjusted R-squared**	0.804
F-statistic	532.288	**Prob (F-statistic)**	0.000	**F-statistic**	511.051	**Prob (F-statistic)**	0.000
DWTS	1.742			**DWTS**	1.788		