Value vs. Growth: Who Leads the Cyclical Stock Market?

Meng Li

Roosevelt University, USA

The market friction theories predict the presence of asymmetric information diffusion between growth and value stocks. This paper provides empirical evidence that growth stocks react to market information faster than value stocks in both up and down market, suggesting that growth stocks are more negatively affected by the worsening market condition, and more favorably affected by the positive market condition. Furthermore, in consistent with the market leadership of growth stocks, the test results show that growth stocks lead value stocks in terms of both mean returns and residual volatilities.

JEL classification: G1
Keywords: value and growth, asymmetric information diffusion, under-reaction

1. Introduction

Since the influential work of Lo and MacKinlay (1990) who document that the returns on large stocks lead those on small stocks but not vice versa, research has offered various explanations for the stock price under-reaction to information, such as incomplete markets and limited stock market participation of neglected firms (Hou and Moskowitz, 2005; Merton, 1987; Shapiro, 2002), transaction costs (Stoll, 2000), information constraints (Peng, 2005) and limited arbitrage (Shleifer and Vishny, 1997; Mendenhall, 2004; Doukas and Li, 2009). While most studies relate the delayed stock price adjustment to the firm specific characteristics, a number of recent research explore the effect of nature of news on speed of price discovery. Hong et al. (2000) uncover that bad news travel slowly, suggesting that slow price adjustment is related to the delayed response to bad news other than good news. Consistent with the hypothesis of slow diffusion of negative information, Hammed and Kusnadi (2006) find that the differential price adjustment between large and small stocks is associated with slow response of small stocks to bad news only. Hou (2007) also shows that the lead-lag pattern between returns of large and small stocks is more significant upon responding to negative news.

Given that major attention has focused on the asymmetric price discovery between different size stocks, it would be interesting to investigate the pricing dynamics of value (high book-to-market ratio) versus growth (low book-to-market ratio) stocks. Although empirical studies reveal that value stocks exhibit greater price delay than growth stocks (Doukas and Li, 2009; Hou and Moskowitz, 2005), two important questions remain: 1) Is the differential price adjustment between value and growth stocks conditional on the nature of market news, as with different size stocks? 2) If value stocks tend to react to new information with lags, can we observe lead-lag structure between growth and value stocks?

This study attempts to examine the evidence on these two related questions. First, in order to reveal the impact of nature of market news on different pricing dynamics between value and growth stocks, we add a binary variable for rising and falling market returns to the regression used in Doukas and Li (2009) paper. Our tests show that the differential speed of price adjustment between value and growth stocks is not affected by the inclusion of a binary variable in the equation. And the comparison of market performance of value vs. growth stocks during large up and down market shows that the returns of growth stocks are more negatively affected by the worsening market condition, and are more positively affected by the improving market condition. These test results suggest that the growth stocks react to new information faster than value stocks regardless of the nature of market news.

Second, since the lead-lag relationship in stock returns is widely considered as evidence of asymmetric speed of information diffusion, the paper tests and confirms the existence of lead-lag relation between growth and value stocks. Specifically, we find that increased (decreased) volatility and mean return of growth stocks are correlated with increased (decreased) volatility and mean return of value stocks but not vice versa, implying a unidirectional information spillover from growth stocks to value stocks.

The rest of the paper is organized as follows. Section 2 reviews the literature on asymmetric information diffusion. Section 3 investigates whether the delayed price adjustment of value stocks is conditional on the nature of market news. Section 4 explores the lead-lag relationship between value and growth. Section 5 concludes.

2. Related Literature

Efficient market is characterized as one in which stock prices reflect instantaneously to the arrival of new information. However, ample empirical studies show that the speed of stock price adjustment varies across stocks, suggesting the existence of market frictions. Lo and MacKinlay (1990) find that the returns of large stocks lead those of smaller stocks. Brennan, Jegadeesh and Swaminathan (1993) find that firms with high analyst coverage tend to respond more rapidly to market returns than do firms with low analyst coverage. Badrinath, Kale and Noe (1995) document that returns of the stocks with the higher level of institutional ownership lead returns of the stocks with the lower levels of institutional ownership. Chordia and Swaminathan (2000) find that stocks with higher trading volume lead stocks with lower trading volume. Most recently, several studies provide evidence that short selling activity enhances the speed of information incorporation into stock prices (Chen and Rhee, 2007; Saffi and Sigurdsson, 2007; Wu, 2008).

With regard to stocks of different book-to-market ratio, Doukas and Li (2009) find that value stock prices exhibit a considerably slow adjustment to market information. They argue that values tocks are exposed to high arbitrage risk, which prevents arbitrageurs from immediately forcing prices to fundamental values. Hou and Moskowitz (2005) also document that value stocks display greater price delay than growth stocks. They attribute the delayed price adjustment to the limited stock market participation associated with value stocks.

While aforementioned papers attribute differential pricing dynamics across stocks to firm specific characteristics, recent papers explore how the speed of price adjustment relates to the state of the market. Hong et al. (2000) unveil that negative information travels slowly. Consistently, some empirical work documents delayed response of small stocks to bad but not to good market information (Hameed and Kusnadi, 2006; Hou, 2007; Chiang et al. 2008). Other empirical work, however, provides opposing evidence that small stocks respond slowly to good but not to bad market news (McQueen et al. 1996).

The documentation of conditional asymmetry in price adjustment between large and small stocks motives the current study. Specifically, we investigate how the different speed of price discovery between value and growth stocks is influenced by the nature of market news.

3. Unconditional Asymmetry of Information Diffusion between Value and Growth Stocks

3.1. Data and Methodology

Following Davis, Fama and French (2000), portfolios are constructed in a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. Controlling firm size is to recognize the asymmetric price adjustment between large and small stocks documented by Lo and MacKinlay (1990). All returns are calculated in excess of the Treasury bill rate from Ibbotson Associates. Market return is value-weighted return on all NYSE, AMEX, and NASDAQ stocks with book equity data for the previous calendar year. To be consistent with earlier studies in the asymmetric information assimilation literature (Lo and MacKinlay 1990, Conrad, Gultekin and Kaul 1991, Jegadeesh and Titman 1995), empirical tests presented in the paper use weekly return data. One advantage of using weekly returns rather than daily returns is that the positive cross-autocorrelation generated by different nontrading probabilities for different portfolio groups is virtually eliminated. Whereas the monthly returns would represent too long a time span to measure the speed of adjustment to new information. The sample includes 2431 weekly observations for each of the 6 size-B/M portfolios. The weekly portfolio return data from July 5, 1963 to January 29, 2010 are from Professor Kenneth French's website.

As in Doukas & Li (2009), we adopt Brennan et al (1993)'s procedure to test whether value stocks react to market information slower than growth stocks. For each size group (small and big), the return on a zero net investment portfolio, which is long in growth portfolio (lowest B/M stocks) and short in value portfolio (highest B/M stocks), is regressed against current and multiple lags of the market return. A positive coefficient on current market return and a negative sum of coefficients on lagged market returns will imply that growth stocks react faster to common information than value stocks. Different from the regressions in Doukas & Li (2009), we include a binary variable to allow parameters to differ when the market is up (Rm>0) or down (Rm<0) as follows:

$$R_{g,t} - R_{v,t} = \alpha + \beta_0 R_{m,t} + \delta R_{m,t} I_t + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \varepsilon_t \tag{1}$$

$$h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1}$$

GARCH specification is employed in the regressions to capture the time-varying idiosyncratic volatility. R(g, t) and R(v,t) are the contemporaneous excess returns of the lowest (growth) and highest B/M (value) portfolios. b(0) is the current beta and ∑ b(-1, -k) refers to the sum of lagged betas. Regressions are fitted with 3 and 5 lags (k=3, 5). We define I(t) = 1 if positive market return shocks (Rm>0) and I(t) = 0 if negative market return shocks (Rm<0). To be consistent with the conjecture that growth stocks react faster to common information than value stocks, we expect to find significant positive b(0), the coefficient on current market returns, and negative ∑ b(-1, -k) , the sum of coefficients on lagged market returns. If the differential price adjustment is conditional on up or down market, we expect to find significant δ .

3.2. Regression Results

Table 1 reports the regression estimation results. The positive coefficients of the current market returns b(0) are significant for all size groups for both 3 and 5 lags, indicating that growth stocks are more sensitive to contemporaneous market returns than are value stocks. Furthermore, the negative sums of coefficients on lagged market returns are significant for all size groups for both 3 and 5 lags. For example, in the lag 3 regression, ∑ b(-1, -k) is -0.0067 and -0.0549 for small and big stocks respectively. Not only are the sums of the lagged coefficients negative, we find all the significant lagged market betas are negative. The negative lagged coefficients combined with positive current coefficients reliably imply that growth stocks react to common information faster than value stocks.

More importantly, binary variables are not significant for any size group and any lag regression, indicating that the greater responsiveness of growth stocks to market information relative to value stocks is not conditional on the state of market.

3.3. Robustness Tests

In addition to the above regressions, where return differentials between growth and value stocks serve as the dependent variables, we also regress the B/M portfolio returns on concurrent and lagged market returns for value and growth portfolios separately as follows:

$$R_{v,t} = \alpha + \beta_0 R_{m,t} + \delta R_{m.t} I_t + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \varepsilon_t \tag{2}$$

and $h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1}$

Table 1
Regressions of zero net investment on value-weighted market returns
(July 5, 1963 - January 29, 2010)

	A. 3 lags		B. 5 lags	
	Small	Big	Small	Big
α	-0.1090**	-0.0828*	-0.1082**	-0.0880**
b(0)	0.2809**	0.1415**	0.2813**	0.1392**
d	-0.0160	0.0295	-0.0165	0.0349
b(-1)	0.0149	-0.0478**	0.0147	-0.0468**
b(-2)	-0.0274**	-0.0279*	-0.0277**	-0.0275*
b(-3)	0.0058	0.0208	0.0059	0.0202
b(-4)			0.0069	-0.0095
b(-5)			-0.0062	0.0180
$\sum_{k=1}^{k} \beta_{-k}$	-0.0067**	-0.0549**	-0.0064**	-0.0456**
a	0.0185**	0.0427**	0.0187**	0.0418**
b	0.1190**	0.095**	0.1195**	0.0944**
c	0.8690**	0.882**	0.8683**	0.8833**

Notes: Table 1 reports the results from regressing the difference between the weekly returns on growth and value portfolios within each size group, on value-weighted market returns:

$$R_{g,t} - R_{v,t} = \alpha + \beta_0 R_{m,t} + \delta R_{m,t} I_t + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \varepsilon_t \quad , \quad h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1} \tag{1}$$

R(g, t) and R(v, t) are the contemporaneous excess returns of the lowest (growth) and highest B/M (value) portfolios. b(0) is the current beta and ∑ b(-1, -k) refers to the sum of lagged betas. I(t)= 1 if positive market return shocks (Rm>0) and I(t)= 0 if negative market return shocks (Rm<0). Regressions are fitted with 3 and 5 lags (k=3, 5). The weekly returns data are from Professor Kenneth French's website. Portfolios are constructed in a two-by-three sort on size and BE/ME. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year end in t-1 divided by market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. * for 5% level. ** for 1% level.

$$R_{g,t} = \alpha + \beta_0 R_{m,t} + \delta R_{m,t} I_t + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \varepsilon_t \tag{3}$$

$$h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1}$$

where R(g, t) and R(v,t) are the contemporaneous excess returns of the lowest (growth) and highest B/M (value) portfolios. b(0) is the current beta and b(-k) refers to the lagged betas. Regressions are fitted with 3 lags (k=3). We recognize through the binary variable I(t) that positive and negative market return shocks may have asymmetric impact on the B/M portfolio returns. I(t) = 1 if positive market return shocks (Rm>0) and I(t) = 0 if negative market return shocks (Rm<0).

Panel A of Table 2 reports the GARCH estimation results for value and growth portfolio returns respectively. The binary variables for market condition are significant for all size and B/M portfolios returns, therefore we calculate current betas for up market as b(0) + d, and current betas for down market as b(0). Clear patterns emerge from comparison of b(DN) and b(UP) across size and B/M portfolios. First, consistent with the finding of unconditional price adjustment differential, both b(DN) and b(UP) are higher for growth stocks than for value stocks. For example, for small stocks, b(DN) of growth stocks (1.1931) is greater than b(DN) of value stocks (0.92775); and b(UP) of growth stocks (1.0651) is again greater than b(UP) of value stocks (0.7122). The same pattern holds with large stocks. Second, regardless of value or growth, small stocks have higher b(DN) than large stocks, and large stocks have higher b(UP) than small stocks, suggesting that small stocks tend to react more strongly to negative market shocks than large stocks, whereas large stocks tend to react more strongly to positive market shocks than small stocks. This finding is consistent with the documentation that delayed price adjustment of small stocks is associated with their slow response to good, but not to bad common information (McQueen, Pinegar, and Thorley, 1996).

Table 2
Regressions of B/M portfolio weekly returns on value-weighted market returns
(July 5, 1963 – January 29, 2010)

Panel A: Regression Results

	Small		Big	
	Eq. (2)	Eq. (3)	Eq. (2)	Eq. (3)
α	0.3450**	0.1580**	0.1447**	0.0511**
b(0)	0.9275**	1.1931**	0.8949**	1.0304**
d	-0.2153**	-0.1280**	0.0361*	0.0550**
b(-1)	0.1579**	0.1662**	-0.0049	-0.0416**
b(-2)	0.0316**	0.0218*	0.0052	-0.0184**
b(-3)	0.0252**	0.0349**	-0.0235**	-0.0050
a	0.0398**	0.0389**	0.0135**	0.0043**
b	0.1300**	0.0795**	0.0968**	0.0912**
c	0.8402**	0.8955**	0.8900**	0.8992**
b(DN)	0.9275	1.1931	0.8949	1.0304
b(UP)	0.7122	1.0651	0.9310	1.0854
Panel B: Mean Portfolio Returns During Large up and down Market Weeks				
Up Market	3.1052	3.8796	3.5361	4.0569
Down Market	-3.5174	-4.8462	-3.3886	-3.9844

Notes: Table 2 reports the results from regressing the weekly returns of growth and value portfolios within each size group, on value-weighted market returns:

$$R_{v,t} = \alpha + \beta_0 R_{m,t} + \delta R_{m,t} I_t + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \varepsilon_t \text{ , } h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1} \quad (2)$$

$$R_{g,t} = \alpha + \beta_0 R_{m,t} + \delta R_{m,t} I_t + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \varepsilon_t \text{ , } h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1} \quad (3)$$

R(g, t) and R(v, t) are the contemporaneous excess returns of the lowest (growth) and highest B/M (value) portfolios. b(0) is the current beta and b(-k) refers to the lagged betas. I(t)= 1 if positive market return shocks (Rm>0) and I(t)= 0 if negative market return shocks (Rm<0). The regressions are fitted with 3 lags (k=3). b(DN) = b(0) is the concurrent beta in down market. b(UP) = b(0)+δ is the concurrent beta in up market. The weekly returns data are from Professor Kenneth French's website. Portfolios are constructed in a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. Large up market week is defined as a week where market return is larger in magnitude than 90% of all the weekly return observations. Large down market week is defined as a week there market return is smaller in magnitude than 10% of all the weekly return observations. * for 5% level. ** for 1% level.

Panel B reports mean returns of size and B/M portfolios during the large up market and large down market weeks. Large up market week is defined as a week where market return is larger in magnitude than 90% of all the weekly return observations. Large down market week is defined as a week there market return is smaller in magnitude than 10% of all the weekly return observations. Consistent with the conjecture developed through beta comparison in Panel A, big growth stocks and small value stocks have the highest (4.05) and the lowest (3.10) mean returns during large up market weeks, and small growth stocks and big value stocks have the lowest (-4.85) and the highest (-3.39) mean returns during large down market weeks. Therefore, the patterns emerged from both Panel A and B can be summarized as follows: In recession, the returns of small growth stocks are most strongly affected, and the returns of big value stocks are least affected; In expansion, the returns of big growth stocks are most favorably affected, and the returns of small value stocks are least favorably affected.

The robustness test provides consistent evidence that the different price adjustment between value and growth stocks is not conditional on the state of the market, whereas small stocks delay in reacting to good news only.

4. The Lead-Lag Structure between Growth and Value Stocks

Section 2 shows that growth stocks react to market information faster than value stocks regardless of the nature of the market information. The asymmetric price adjustment can be reflected not only in the lead-lag relation of mean returns, but also in unidirectional volatility spillover between portfolio returns. Ross (1989) shows that the variance of price changes is related directly to the rate of flow of information. Bollerslev et al (1992) show that speculative price changes are interwoven with higher moment dependencies. Cheung and Ng (1996) also argue that volatility spillovers are important because changes in volatility reflect the arrival of information. That is, if the return volatility of portfolio A has an impact on the return volatility of portfolio B, whereas the return volatility of portfolio B has no impact on the return volatility of portfolio A, then the conclusion can be made that the portfolio A react to new information faster than portfolio B. Using the GARCH family of statistical processes, Conrad, Gultekin and Kaul (1991) find that the volatility shocks to larger firms are important to the future dynamics of the returns of smaller firms as well as to their own returns. Conversely, the volatility shocks to smaller firms have no impact on either the conditional mean or the variance of the returns of larger firms, therefore confirming the asymmetric information diffusion between large and small stocks. To be consistent with the literature, we not only test the leadership of growth stocks in terms of mean returns, but the unidirectional volatility spillover from growth to value stocks.

4.1. Growth Stocks Lead Value Stocks in Terms of Mean Returns

To investigate the lead-lag relations in the weekly returns we estimate the following regression as suggested by Badrinath, et al (1995).

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \beta_{-2} R_{g,t-2} + \beta_{-3} R_{g,t-3} + \varepsilon_t \tag{4}$$

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \beta_{-2} R_{v,t-2} + \beta_{-3} R_{v,t-3} + \varepsilon_t \tag{5}$$

Where R(g, t) and R(v, t) are the contemporaneous excess returns of the lowest and highest B/M portfolios. R(g, t-i) and R(v, t-i) are the excess return i weeks earlier on growth and value portfolios, i = 1, 2, 3 in our regressions. Contemporaneous and lagged returns of the lowest B/M (growth) portfolio are predictors for returns of the highest B/M (value) portfolio in Eq.(4); Contemporaneous and lagged returns of the highest B/M (value) portfolio are predictors for returns of the lowest B/M (growth) portfolio in Eq.(5). To be consistent with our hypothesis that growth stock returns lead value stock returns, we expect to find that one or more of the coefficients of the lagged growth portfolio returns in Eq.(4) are positive significant, whereas the coefficients of the lagged value portfolio returns in Eq.(5) are insignificant or less significant than the coefficients in Eq.(4).

Table 3 reports the estimation results. As expected, we find a significant positive correlation between contemporaneous value weekly returns and one week lagged growth returns for both size groups. By contrast, we find significant negative correlation between contemporaneous growth weekly returns and one week lagged value returns for both size groups. The existence of the significant positive correlation between the lagged growth returns and the contemporaneous value returns supports the hypothesis that growth stock returns lead the value stock returns. Furthermore, the finding of negative correlation between the lagged value returns and the contemporaneous growth returns rejects the existence of a feed-back relationship, in which growth returns lead (cause) value returns, and simultaneously value returns lead (cause) growth returns. Thus the finding lends further support to the unidirectional lead-lag hypothesis between growth and value stocks.

Table 3
The cross-correlation between the lowest and highest B/M portfolio weekly returns
(July 5, 1963 – January 29, 2010)

	Small		Big	
	Eq. (4)	Eq. (5)	Eq. (4)	Eq. (5)
α	0.1769**	-0.1520**	0.0944**	0.0026
b(0)	0.7203**	1.1291**	0.7783**	0.8101**
b(-1)	0.0190**	-0.0364**	0.0328**	-0.0444**
b(-2)	0.0118	-0.0271*	0.0134	-0.0217
b(-3)	-0.0081	-0.0009	-0.0266*	0.0198

Notes: Table 3 reports the cross-correlations between the lowest and highest B/M portfolio weekly returns estimated from the regression below:

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \beta_{-2} R_{g,t-2} + \beta_{-3} R_{g,t-3} + \varepsilon_t \quad (4), \quad R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \beta_{-2} R_{v,t-2} + \beta_{-3} R_{v,t-3} + \varepsilon_t \quad (5)$$

R(g, t) and R(v,t) are the contemporaneous returns of the lowest (growth) and highest (value) B/M portfolios. R(g, t-i) and R(v, t-i) are the excess returns i weeks earlier on the growth and value portfolios (i = 1, 2, 3). The weekly returns data are from Professor Kenneth French's website. The portfolios are constructed by a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. * for 5% level. ** for 1% level.

4.2. Unidirectional Volatility Spillover

In the spirit of Conrad et al (1991), we first estimate a GARCH(1,1)-M model for lowest B/M (growth) and highest B/M (value) portfolios separately, and then introduce the lagged squared errors of growth and value portfolios as an exogenous variable in conditional variance equations of value and growth portfolios respectively. If growth stocks indeed react to new information faster than value stocks do, we expect to show that lagged squared errors of growth portfolios play a significant role in determining the conditional variance of value portfolios, but not vice versa.

To be consistent with the models used to test mean return spillover (Eq. (4) and (5)), we also include concurrent and lagged returns of the other portfolio in the mean return equations. Inclusion of lagged returns of the other portfolio in the mean return equations ensures that all asymmetry in the predictability of mean returns is purged from the error terms. This is important because the asymmetric spillover in mean returns remained in the error term could show up as asymmetric responses of conditional variances to shocks. The estimated models are:

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \gamma \sigma_{v,t} + \varepsilon_{v,t} \quad (6)$$
$$h_{v,t} = a + b\varepsilon^2_{v,t-1} + ch_{v,t-1}$$

and

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \gamma \sigma_{g,t} + \varepsilon_{g,t} \quad (7)$$
$$h_{g,t} = a + b\varepsilon^2_{g,t-1} + ch_{g,t-1}$$

where R(g, t) and R(v,t) are the contemporaneous excess returns of the lowest and highest B/M portfolios. R(g, t-1) and R(v, t-1) are the excess return 1 week earlier on growth and value portfolios. b(-1) measures the impact of the lagged returns of the growth (value) portfolio on the conditional mean of the value (growth) portfolio. *S* is the standard deviation of the conditional variance of the error term.

We interpret the squared residuals derived from Eq. (6) and (7) as a "volatility shock" to value and growth stocks respectively. The "volatility shock" variables are then appended to the conditional variance of Eq.(7) and (6) as shown in following specification, to estimate the impact of the volatility shocks to value (growth) portfolio returns on the conditional variance of growth (value) portfolio returns.

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \gamma\sigma_{v,t} + \varepsilon_{v,t} \qquad (8)$$
$$h_{v,t} = a + b\varepsilon^2_{v,t-1} + ch_{v,t-1} + d\varepsilon^2_{g,t-1}$$

and

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \gamma\sigma_{g,t} + \varepsilon_{g,t} \qquad (9)$$
$$h_{g,t} = a + b\varepsilon^2_{g,t-1} + ch_{g,t-1} + d\varepsilon^2_{v,t-1}$$

d measures the impact of past volatility surprises to the growth portfolio on the conditional variance of the value portfolio in Eq.(8), and in Eq.(9), *d* measures the impact of past volatility surprises to the value portfolio on the conditional variance of the growth portfolio. The volatility surprises, $e^2_{g,t-1}$ and $e^2_{v,t-1}$ are lagged squared residuals derived from Eq. (7) and (6) respectively.

Table 4
The volatility spillover between the lowest and highest B/M portfolio weekly returns
(July 5, 1963 – January 29, 2010)

	Small		Big	
	Eq. [8]	Eq. [9]	Eq. [8]	Eq. [9]
α	0.0517	0.0065	-0.0653	0.0412
b(0)	0.6992**	1.1688**	0.7403**	0.8409**
b(-1)	0.0298**	-0.0477**	0.0222*	-0.0486**
g	0.1525*	-0.1423*	0.1615*	-0.0304
a	0.0183**	0.0171**	0.0333**	0.0369**
b	0.1056**	0.0976**	0.0793**	0.1097**
c	0.8552**	0.8806**	0.8839**	0.8647**
d	0.0125**	0.0218	0.0133**	0.0104*

Notes: Table 4 reports the volatility spillover between the lowest and highest B/M portfolio weekly returns using GARCH-M model

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \gamma\sigma_{v,t} + \varepsilon_{v,t}\,, \quad h_{v,t} = a + b\varepsilon^2_{v,t-1} + ch_{v,t-1} + d\varepsilon^2_{g,t-1} \qquad (8)$$

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \gamma\sigma_{g,t} + \varepsilon_{g,t}\,, \quad h_{g,t} = a + b\varepsilon^2_{g,t-1} + ch_{g,t-1} + d\varepsilon^2_{v,t-1} \qquad (9)$$

R(v, t) and R(g,t) are the contemporaneous returns of the value and growth portfolios. R(v, t-1) and R(g, t-1) are the excess return 1 week earlier on the value and growth portfolios. *S* is the standard deviation of the conditional variance of the error term. d measures the impact of past volatility surprises to the growth portfolio on the conditional variance of value portfolio in Eq.[8], and in Eq.[9], d measures the impact of past volatility surprises to the value portfolio on the conditional variance of growth portfolio. The volatility surprises, e^2(g, t-1) and e^2(v, t-1) are lagged squared residuals derived from Eq. [7] and [6] respectively. The weekly returns data are from Professor Kenneth French's website. Portfolios are constructed by a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by the market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. * for 5% level. ** for 1% level.

Table 4 reports the volatility spillover estimation results. Consistent with our expectations, we find a distinct asymmetry in volatility spillover between growth and value portfolios. The coefficients of past volatility surprise to growth portfolio in the conditional variance equation of value portfolio are positive and significant for both small (0.0125) and large stocks (0.0133). And the volatility spillover from growth to value portfolios is translated into the increased value portfolio returns, which is evidenced from the significant GARCH-M terms in the value portfolio mean return equation. By contrast, the past volatility surprise to value portfolio is not significant in determining the conditional variance of growth portfolio for small stocks (0.0218), and only marginally significant for the large stocks (0.0104). Furthermore, the insignificant GARCH-M term in mean return equation of large growth portfolio (-0.0304) indicates that the returns of large growth portfolio are not affected by their conditional variance, and therefore are not affected by the return volatility of value portfolio.

In addition, after introducing volatility spillover effect to the GARCH models, the asymmetry in the predictability of mean returns between growth and value portfolios remains. The coefficients of the lagged growth returns in determining the contemporaneous value returns are consistently positive and significant, whereas the coefficients of the lagged value returns in determining the contemporaneous growth returns are consistently negative and significant. The simultaneous existence of unidirectional mean return and conditional volatility spillover implies that information is spread (with lags) from growth firms to value firms but not vice versa.

5. Conclusion

The paper finds that the returns of growth stocks lead those of value stocks in both up and down market, suggesting that growth stocks are more negatively affected by the worsening market condition, and more favorably affected by the positive market condition. Furthermore, the paper provides evidence of unidirectional spillover of mean returns and conditional volatilities, implying that new market information transmits from growth stock to value stocks but not vice versa.

The paper sheds light on how the state of market impacts the price discovery process of value vs. growth stocks. Although we find value stocks display slow reaction to information in both up and down market, future empirical studies could uncover whether the delayed response is more significant when there is negative information. For instance, Chen and Rhee (2007) find that the difference in speed of price adjustment between shortable and non-shortable stocks is more pronounced in down market. The ultimate challenge, however, is to explain the mechanism under which the state of the market changes the pattern of asymmetric pricing dynamics across stocks.

References:

Badrinath, S.G., J.R. Kale, and T.H. Noe, 1995, Of shepherds, sheep, and the cross-autocorrelation in equity returns. *The Review of Financial Studies* 8, 401-430.

Bollerslev, T. and J.M. Wooldridge, 1992, Quasi-maximum likelihood estimation of dynamic models with time-varying covariances. *Econometric Reviews* 11, 143-172.

Brennan, J.M., N. Jegadeesh, and B. Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information. *The Review of Financial Studies* 6, 799-824.

Chang, E.C., G.R. McQueen, and J.M. Pinegar, 1999, Cross-autocorrelation in Asian Stock markets. *Pacific-Basin Finance Journal* 7, 471-493.

Chen, C.X. and S.G. Rhee, 2007, The impact of short sales on the speed of price adjustment: evidence from the Hong Kong stock market. *Working Paper, University of Hawaii*.

Chiang, T.C., E. Nelling, and L. Tan, 2008, The speed of adjustment to information: evidence from the Chinese stock market. *International Review of Economics and Finance* 17, 216-229.

Cheung, Y.W. and L. K. Ng, 1996, A causality-in-variance test and its implications to financial market prices. *Journal of Econometrics* 72, 33-48.

Chordia, T. and B. Swaminathan, 2000, Trading volume and cross-autocorrelations in stock returns. *Journal of Finance* 55, 913-935.

Conrad, J., M.N. Gultekin, and G. Kaul, 1991, Asymmetric predictability of conditional variances. *The Review of Financial Studies* 4, 597-622.

Conrad, J., B. Cornell, and W. Landsman, 2002, When is bad news really bad news? *Journal of Finance* 57, 2507-2532.

Doukas J. and M. Li, 2009, Asymmetric asset price reaction to news and arbitrage risk. *Review of Behavioral Finance* 1, 23-43.

Gulen, H., Y. Xing, and L. Zhang, 2008, Value versus growth: time-varying expected stock returns. *Financial Management* Forthcoming.

Hameed, A. and Y. Kusnadi, 2006, Stock returns cross-autocorrelations and market conditions in Japan. *Journal of Business* 79, 3029-3056.

Hong, H., T. Lim, and J.C. Stein, 2000, Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance* 55, 265-295.

Hou, K., 2007, Industry information diffusion and the lead-lag effect in stock returns. *Review of Financial Studies* 20, 1113-1138.

Hou, K. and T.J. Moskowitz, 2005, Market frictions, price delays, and the cross-section of expected returns. *The Reviews of Financial Studies* 18, 981-1020.

Jegadeesh, N and S. Titman, 1995, Overreaction, delayed reaction, and contrarian profits. *The Reviews of Financial Studies* 8, 973-993.

Lo, A.W., and A.C. MacKinlay, 1990, When are contrarian profits due to stock market overreaction? *Review of Financial Studies* 3, 175-206.

Mendenhall, R., 2004, Arbitrage risk and post-earnings announcement drift. *Journal of Business* 77, 875-894.

McQueen, G., M. Pinegar, and S. Thorley, 1996, Delayed reaction to good News and the gross-autocorrelation of portfolio returns. *Journal of Finance* 51, 889-919.

Merton, R.C., 1987, A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42, 483-510.

Peng, L., 2005, Learning with information capacity constraints. *Journal of Financial and Quantitative Analysis* 40(2), 307-329.

Ross, S.A., 1989, Information and volatility: the no-arbitrage martingale approach to timing and resolution irrelevancy. *Journal of Finance* 44, 1-17.

Saffi, P.A.C., and K. Sigurdsson, 2007, Price efficiency and short-selling. *SSRN working paper*

Shapiro, A., 2002, The investor recognition hypothesis in a dynamic general equilibrium: theory and evidence. *Review of Financial Studies* 15, 97-141.

Shleifer, A. and R. Vishny, 1997, The limits of arbitrage. *Journal of Finance* 52(1), 35-55.
Stoll, H.R., 2000, Friction. *Journal of Finance* 55(4), 1479-1514.
Wu, J.J., 2008, Short selling and the informational efficiency of prices. *SSRN working papers.*