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Stock Reaction to Market-Wide Information

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Introduction

Investor reaction to information as well as whether securities are rationally priced has been a topic of considerable interest for over a century.[1] Inconsistent with the early evidence supporting the efficient market hypothesis surveyed in Fama (1970), more recent US and international evidence suggests that stock returns exhibit short-term momentum and long-term reversals,[2] and that investors tend to under-react to *firm-specific* news at short horizons and over-react at longer horizons.[3]

Motivated by these empirical findings, Barberis, Shleifer, and Vishny (1998) (BSV), Daniel, Hirshleifer, and Subrahmanyam (1998) (DHS) and Hong and Stein (1999) (HS) propose behavioral asset-pricing models that attempt to explain these perceived anomalies. The models in BSV and DHS emphasize cognitive investor biases and predict that asset mis-valuation should be greatest among firms with greater degrees of uncertainty and poor information. HS emphasize gradual information diffusion and predict that slower information diffusion generates more mis-valuation. Daniel and Titman (2006) show recently that stocks mainly mis-react to intangible information not tangible information.

The behavioral theories usually do not distinguish between firm-specific and market-wide information. Intuitively, it is also unlikely that investors would systematically mis-react to (intangible) firm-specific news, but correctly understand (intangible) market-wide information. Inexplicably, there is as yet no evidence suggesting that stocks under-react to common information at short horizons and over-react at longer horizons. Lo and MacKinlay (1990) and Jegadeesh and Titman (1995) find a size-related lead-lag relationship in stock returns which suggests that (small) stocks under-react to market-wide information in the short run (one week to one month). Lewellen (2002) documents an average negative cross-serial correlation for lags from 1 to 30 months, which may suggest that stocks over-react to market-wide information at

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[1] Fama (1976) credits Bachelier (1900) with postulating the hypothesis that price changes are random.

[2] See Jegadeesh and Titman (1993), Rouwenhorst (1998), Chan, Hameed and Tong (2000), Moskowitz and Grinblatt (1999), Jegadeesh and Titman (2001), and Lewellen (2002) for US as well as international stock momentum evidence. See DeBondt and Thaler (1987), Fama and French (1988), Poterba and Summers (1988), Alonso and Rubio (1990), da Costa's (1995), Clare and Thomas (1995), and Balvers, Wu, and Gilliland (2000) for US and international stock reversal evidence.

[3] For instance, Bernard and Thomas (1989, 1990), and Brown and Pope (1996) find short-run under-reaction to earnings announcements, while DeBondt and Thaler (1987) and Lakonishok, Shleifer, and Vishny (1994) find a negative relationship between long-horizon returns and past financial performance measures such as earnings or sales growth. See Daniel, Hirshleifer, and Subrahmanyam (1998) for an overview.

both short and long horizons.[4] Recently, Kothari, Lewellen, and Warner (2006) examine whether the stock market as a whole mis-reacts to aggregate earnings surprises. They find no evidence of market mis-reaction to such news. Given the strong correlation between aggregate earnings and macro variables such as industrial production, GDP and consumption, their findings suggest that the market as a whole does not mis-react to common information.[5]

Given the popularity of the behavioral models, a lack of mis-reaction to common information would be an anomaly within this anomaly literature. This observation motivates us to revisit the issue of stock reaction to common information. We find that the no-mis-reaction result of Kothari, Lewellen, and Warner (2006) may be mainly due to their focus on the market level reaction, not stock level reaction. In fact, that stocks mis-react to common information may not necessarily imply that the stock market as a whole will also mis-react to common information. This logically follows because only stocks with considerable uncertainty or slow information diffusion (i.e. small stocks) may exhibit the under- and/or over-reaction patterns predicted by the behavioral models. If proportionally they represent a relatively small segment of the stock market in terms of their capitalization, the reaction pattern may not be evident at the market level. Motivated by this observation, we focus on stock reaction to common information at the stock level in this manuscript.

We follow Jegadeesh and Titman (1995) and use a regression-based approach to examine the short-run and long-run reaction of stocks to common information. The behavioral models predict that only stocks with poor information/more uncertainty or slow information diffusion will have systematic mis-reaction, i.e. small-cap stocks [see Hong, Lim, and Stein (2000)] or stocks in cyclical industries (which have significant uncertainty). Thus, we focus on two sets of US portfolios: size-sorted portfolios and industry portfolios. We find a statistically and economically significant reaction pattern to common information as the behavioral models suggest. This finding thus complements the findings of stock mis-reaction to firm-specific information, and should benefit researchers attempting to understand investor behavior.

Furthermore, we find that the Fama-French size factor seems to proxy this delayed reaction to common information well, and that the delayed reaction to common information is primarily due to mis-reaction to intangible common information. Considered together, our results

[4] See Appendix for a detailed discussion.

[5] Flannery and Protopapadakis (2002), Boyd, Hu and Jagannathan (2005), Bernanke and Kuttner (2005), and Ferreira and Gama (2007) study whether the aggregate stock market reacts to macro news, not whether it mis-reacts. Brennan, Jegadeesh, and Swaminathan (1993) study stock reaction to common information; but they focus on daily data in the short run.

also supplement Vassalou (2003) and suggest that the size factor may not only proxy future economic growth, but also the delayed reaction to the news related to future economic growth.

The remainder of the paper is organized as follows. Section 1 discusses the motivation of the paper. Section 2 presents the empirical methodology. Section 3 describes the data and presents the empirical results. Section 4 concludes the paper with a brief summary.

1. Motivation

The popular behavioral models predict that *only* stocks with poor information/more uncertainty or slow information diffusion will have systematic mis-valuation, i.e. small-cap stocks [see Hong, Lim, and Stein (2000)] or stocks in cyclical industries. Therefore, it is possible that the mis-valuation they predict may exist at the security level, but not at the market level. To see this, suppose there are two securities in the economy: one ($r_{1,t}$) has systematic misevaluation and the other ($r_{2,t}$) does not have. Their return-generating processes are

$$r_{1,t} = \mu_1 + \sum_{k=0}^{K} b_{1,k} f_{t-k} + e_{1,t} \tag{1a}$$

$$r_{2,t} = \mu_2 + b_{2,0} f_t + e_{2,t} \tag{1b}$$

where $r_{i,t}$ is the return of asset *i* at time *t*, μ_i is a constant, f_{t-k} is the market-wide information at time *t* - *k*, $e_{i,t}$ is the firm-specific information at time *t*, and $b_{i,k}$ is the sensitivity of stock *i* to the common information.[6] Equation (1a) allows stock returns to react instantaneously as well as with multiple lags to common information. This formulation is essentially a generalization of Jegadeesh and Titman (1995), who allow one lag. Equation (1b) is a standard one-factor single-period model.

Since f_{t-k} is defined as common information, $\text{cov}(f_t, f_{t-k}) = 0$, and since $e_{i,t}$ is defined as the firm-specific information, $\text{cov}(e_{i,t}, e_{j,t-k}) = \text{cov}(f_t, e_{i,t-k}) = 0 \, \forall i \neq j$. The stock reaction to the common information is measured by $b_{i,k}$ for *k* = 0, …, *K*. If there is no systematic under- and/or over-reaction to the common information, $b_{i,k} = 0 \; for \; k = 1, 2, \ldots, K$. Thus, Equation (1b) is consistent with no mis-valuation. However, if stocks under-react (delayed over-react) in the short run and over-react in the longer run to market-wide information, $b_{i,k} > 0$ for

[6] As in Jegadeesh and Titman (1995), we assume the factor sensitivities are constant and uncorrelated with factor realizations.

some small *k* and $b_{i,k} < 0$ for some large *k*. Consequently, Equation (1a) is consistent with the behavioral models.

Now consider the value-weighted market return, $r_{M,t}$

$$
\begin{aligned}
r_{M,t} &= s_1 r_{1,t} + s_2 r_{2,t} \\
&= s_1(\mu_1 + \sum_{k=0}^{K} b_{1,k} f_{t-k} + e_{1,t}) + s_2(\mu_2 + b_{2,0} f_t + e_{2,t}) \\
&= s_1\mu_1 + s_2\mu_2 + (s_1 b_{1,0} + s_2 b_{2,0}) f_t + \sum_{k=1}^{K} s_1 b_{1,k} f_{t-k} + s_1 e_{1,t} + s_2 e_{2,t} \qquad (2)
\end{aligned}
$$

where s_1 and s_2 are their weights based on their market capitalization. $b_{i,k}$ for $k \neq 0$ should be very small., because if there is any mis-valuation, it should be very small in magnitude such that investors may not easily observe this mis-valuation and arbitrage opportunity. [Poterba and Summers (1988)].[7] Therefore, it is evident if s_1 is also relatively small, $s_1 b_{1,k}$ should be very close to zero. Then, we have

$$
r_{M,t} \approx (s_1\mu_1 + s_2\mu_2) + (s_1 b_{1,0} + s_2 b_{2,0}) f_t + (s_1 e_{1,t} + s_2 e_{2,t}) \qquad (3)
$$

Since $e_{1,t}$ and $e_{2,t}$ are firm-specific information, e_t should be very close to white noise. Therefore, even though the market level returns do not under- or over-react to common information, at the security level under- or over-reaction may still exist. This observation motivates our examination of stock reaction to common information at the security level.

2. Empirical Methodology

We do not use macroeconomic variables as Chordia and Shivakumar (2002) do to proxy common information. We argue that it may be more advantageous to use mimicking portfolios (i.e. the market return) to proxy common information instead of using the economic variables directly. As Vassalou (2003) points out, economic variables may contain information that is irrelevant for asset pricing and may also have measurement errors. Further, only the unexpected component of macroeconomic variables contains news that is relevant for asset pricing. To obtain the unexpected component, some specification of a structural or statistical model of investor expectation is necessary. If any such model has specification error, test results based on the model will be unreliable.[8] In contrast, it is well-known that the value-weighted market index follows a

[7] For instance Jegadeesh and Titman (1995) find on average $b_{i,1} = 0.16$.

[8] This well-known problem is called the "bad model problem" by Fama (1998).

random walk (see Lo and MacKinlay (1988)), suggestive that market returns do not under or over-react to common information. Kothari, Lewellen, and Warner (2006) reinforce this observation by demonstrating that market returns do not mis-react to aggregate earnings surprises. Thus, if there is any macro information relevant for asset pricing, the stock market as a whole will react correctly or at least very close to correctly, and consequently, the value-weighted market return is itself a good summary proxy for all relevant common information. Brennan, Jegadeesh, and Swaminathan (1993) concisely point out that "(t)he market return may be viewed as a linear combination of the contemporaneous common factors" (p809). This same intuition also motives Jegadeesh and Titman (1995) to use the market return as the proxy for common information.

To examine the stock reaction to common information, we estimate Equation (1a) directly as in Jegadeesh and Titman (1995). We use the value-weighted market return as the summary proxy for all relevant common information. Motivated by the momentum and reversal findings of Jegadeesh and Titman (1993), we include lagged market returns for up to two years.[9] If we allow lagged market returns for up to two years and estimate Equation (1a) directly, the test may lack power, because each individual $b_{i,k}$ may be very small in magnitude. To increase statistical power, we instead estimate the following model for each asset.

$$r_{i,t} = \mu_i + b_{i,0} f_t + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k=13}^{24} f_{t-k} + e_{i,t} \tag{4}$$

This specification will not result in a loss of information, because what are relevant are the signs rather than the magnitudes of $b_{i,k}$. The behavioral models predict that $b_{i,k}$ may have different signs over different horizons. To consider this, we choose one month, one year, and two years. These seem to be natural intervals and are widely used in the literature [see Poterba and Summers (1988)]. If investors under-react at short horizons and over-react at longer horizons to common information as the behavioral models predict, coefficients of lagged market returns should be significantly positive at some short horizons and negative at some longer horizons.

3. Data and Empirical Results

3.1 Data

Following Lewellen (2002), we focus on the post Great Depression period, January 1941 to August 2007. The behavioral models predict that only stocks with poor information/more

[9] Jegadeesh and Titman (1993) suggest that it may take two years for the market to fully incorporate information.

uncertainty or slow information diffusion will have systematic mis-valuation, i.e. small-cap stocks [see Hong, Lim, and Stein (2000)] or stocks in cyclical industries. Thus, we focus on 10 size-sorted portfolios and 10 industry portfolios for empirical investigation. The monthly equal-weighted return data are downloaded from Kenneth French's website.[10] Table 1 reports the summary statistics of the portfolio returns, with average return and variance for each portfolio and each portfolio's beta with the market index.

Table 1 Summary Statistics: 1941:01-2007:08

	Mean	Variance	CAPM β
Small 1	0.0148	0.0047	1.1502
2	0.0111	0.0038	1.2413
3	0.0113	0.0033	1.2204
4	0.0107	0.0031	1.1992
5	0.0108	0.0029	1.1800
6	0.0104	0.0026	1.1429
7	0.0107	0.0024	1.1310
8	0.0101	0.0023	1.1056
9	0.0100	0.0020	1.0291
big 10	0.0086	0.0018	0.9879
NoDur	0.0105	0.0024	0.9546
Durbl	0.0101	0.0038	1.2035
Manuf	0.0114	0.0029	1.1172
Energy	0.0133	0.0042	1.0431
HiTec	0.0117	0.0058	1.4786
Telcm	0.0118	0.0044	1.2457
Shops	0.0109	0.0030	1.0682
Hlth	0.0133	0.0041	1.2055
Utils	0.0110	0.0017	0.6327
Other	0.0126	0.0030	1.0555

3.2 Under- and Over-reaction to Common Information

The behavioral models predict that small-cap stocks may have stronger mis-valuation than large-cap stocks due to poor information or slow information diffusion [see Hong, Lim, and Stein (2000)]. Consequently, we should expect small-cap stocks to have stronger under-reaction at short horizons and over-reaction at longer horizons to information than large-cap stocks. Table 2 reports $b_{i,k}$ estimates and associated t-statistics for returns of 10 size-sorted portfolios. The values reported in the main rows are the actual values of $b_{i,k}$ estimates, and the entries below are the Newey-West test statistics. As we can see, $b_{i,1}$, the sensitivity of stock returns to common

[10] We thank Fama and French for making these data available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

information at lag 1, is generally positive, while $b_{i,2}$ and $b_{i,3}$, the sensitivities to common information at lags 2 to 24, are generally negative.[11] This suggests that stocks generally under-react at short horizons (one month lag) and overreact at longer horizons. Furthermore, $b_{i,k}$ estimates tend to decrease in magnitude as the size increases, suggesting that smaller stocks have stronger under-reaction at short horizons and over-reaction at longer horizons. These results seem to support the behavioral models.

Table 2 Size Portfolios 1941:01-2007:-8

We estimate the following model for each size-sorted portfolio.

$$r_{i,t} = \mu_i + b_{i,0} f_t + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k13}^{24} f_{t-k} + e_{i,t}$$

where $r_{i,t}$ is the return of asset *i* at time *t*, f_{t-k} is the market-wide information at time *t* – *k* measured by the value-weighted market return, and $b_{i,k}$ is the sensitivity of stock *i* to the common information. $b_{i,k}$ estimates are reported in the main rows, with the Newey-West test t-statistics immediately below each main row.

Size	μ_i	$b_{i,0}$	$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$\overline{R}^2$
Small 1	0.007	1.118	**0.342**	-0.022	**-0.035**	0.538
	2.45	21.4	7.39	-1.83	-2.86	
2	0.001	1.223	**0.203**	-0.015	**-0.019**	0.728
	0.76	32.84	5.72	-1.66	-2.44	
3	0.002	1.206	**0.150**	**-0.018**	**-0.015**	0.792
	1.39	39.33	5.14	-2.48	-2.53	
4	0.001	1.187	**0.127**	-0.012	**-0.016**	0.812
	0.95	39.85	4.74	-1.78	-2.98	
5	0.002	1.171	**0.093**	**-0.014**	**-0.011**	0.842
	1.44	42.46	4.19	-2.55	-2.30	
6	0.001	1.136	**0.069**	**-0.011**	**-0.009**	0.872
	1.35	46.34	3.3	-2.22	-2.21	
7	0.002	1.125	**0.058**	**-0.012**	**-0.008**	0.908
	1.98	62.08	3.49	-2.71	-2.40	
8	0.001	1.103	0.021	**-0.012**	-0.005	0.923
	2.26	57.54	1.56	-4.10	-1.64	
9	0.002	1.029	-0.001	**-0.008**	-0.002	0.934
	2.94	69.19	-0.09	-3.05	-0.98	
Big 10	-0.001	0.99	**-0.02**	0.001	**0.004**	0.947
	-1.90	59.03	-2.01	0.51	2.22	

Table 3 reports $b_{i,k}$ estimates and associated Newey-West t-statistics for 10 industry portfolios. The results are reported in the same fashion as in Table 2. If the behavioral models are true, we expect that industries with more uncertainty would have a stronger mis-valuation pattern.

[11] The only exception is Decile 10 portfolio.

Our empirical results are largely consistent with this prediction. Again, $b_{i,1}$ is generally positive, while $b_{i,2}$ and $b_{i,3}$ are generally negative. Furthermore, the only industry that does not exhibit this pattern is the Utilities industry, which has the least uncertainty due to regulatory oversight and control.

That stocks under-react to common information at short horizons and over-react at longer horizons is one of the central findings of this paper. This finding complements the findings that stocks under-react to firm-specific information at short horizons and over-react at longer horizons, and should benefit researchers attempting to understand investor behavior.

Table 3 Industry Portfolios 1941:01-2007:08

We estimate the following model for each industry portfolio.

$$r_{i,t} = \mu_i + b_{i,0} f_t + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k13}^{24} f_{t-k} + e_{i,t}$$

where $r_{i,t}$ is the return of asset *i* at time *t*, f_{t-k} is the market-wide information at time *t* – *k* measured by the value-weighted market return, and $b_{i,k}$ is the sensitivity of stock *i* to the common information. $b_{i,k}$ estimates are reported in the main rows, with the Newey-West test t-statistics immediately below each main row.

Industry	μ_i	$b_{i,0}$	$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$\overline{R}^2$
NoDur	0.005	0.935	**0.194**	**-0.018**	**-0.026**	0.701
	2.49	24.08	7.42	-2.09	-3.69	
Durbl	0.001	1.182	**0.233**	-0.013	**-0.023**	0.683
	0.3	25.43	6.38	-1.31	-2.34	
Manuf	0.002	1.102	**0.176**	-0.013	**-0.014**	0.771
	1.37	31.57	6.38	-1.67	-2.17	
Energy	0.005	1.040	0.022	-0.001	-0.009	0.451
	1.69	16.91	0.47	-0.07	-0.74	
HiTec	0.001	1.458	**0.221**	**-0.024**	**-0.022**	0.667
	0.27	23.06	5.41	-2.01	-2.11	
Telcm	0.003	1.228	**0.198**	**-0.024**	-0.016	0.63
	0.97	19.75	5.20	-2.15	-1.58	
Shops	0.003	1.044	**0.260**	-0.016	**-0.024**	0.693
	1.29	27.15	8.53	-1.32	-2.88	
Hlth	0.005	1.188	**0.176**	**-0.025**	**-0.022**	0.636
	2.18	35.11	4.91	-2.07	-2.11	
Utils	0.004	0.633	0.017	0.004	0.005	0.41
	1.93	10.88	0.52	0.53	0.63	
Other	0.005	1.036	**0.207**	**-0.018**	**-0.023**	0.677
	2.39	22.3	6.47	-2.05	-3.00	

3.3 Predictive Power of Past Common Information

The results in Tables 2 and 3 are informative. They show that stocks with more uncertainty or slower information diffusion statistically significantly under-react in the short run and over-react in the long run. The implication is that past common information should have the power to predict stock returns. We test this implication in this section. Examining the predictive power of past common information also provides a measure of the economic significance of the mis-reaction.

Our idea is to use the past common information to predict the stock returns, then long the stocks with the highest predicted returns and short the stocks with the lowest predicted returns. If the delayed reaction is economically significant, the momentum portfolio should generate significant profits. More specifically, at the beginning of each month *t*, we first use the past common information to predict the month-*t* returns. The predicted return, $\hat{r}_{i,t}$, is the one-period ahead forecast from the following forecasting model:

$$r_{i,t} = \mu_i + c_{i,1} f_{t-1} + c_{i,2} \sum_{k=2}^{12} f_{t-k} + c_{i,3} \sum_{k=13}^{24} f_{t-k} + \varepsilon_{i,t} \tag{5}$$

That is $\hat{r}_{i,t} = \hat{c}_{i,1} f_{t-1} + \hat{c}_{i,2} \sum_{k=2}^{12} f_{t-k} + \hat{c}_{i,3} \sum_{k=13}^{24} f_{t-k}$. To obtain meaningful estimates, the coefficients of the model, $c_{i,k}$, are estimated using the previous 24 years of returns. Consequently our test starts in 1965. We choose 1965 as our start date also because the momentum literature usually focuses on this sample period [see for instance Jegadeesh and Titman (1993)]. The coefficients are then used to compute the one-month-ahead predicted return for each asset. We update our estimates of $c_{i,k}$ every month by dropping the earliest observation and adding the latest observation every month in the regression. Based on the predicted returns, size/industry portfolios are then ranked in ascending order. Based on these rankings, we long the top three portfolios (winners) and short the bottom three (losers) in an equally-weighted fashion. These positions are held for one month.

Table 4 presents the results. The momentum (Winner-Loser) profits for the size portfolios are reported in Panel A, and those for the industry portfolios are reported in Panel B. Table 4 also distinguishes between January and other calendar months. Overall, momentum strategies are significantly profitable in both sets of portfolios based on our forecasting model. Excluding January, the average profits for the size and industry portfolio are 0.95% per month (t-statistic of 7.65), and 0.73% per month (t-statistic of 3.92), respectively.

Table 4 Momentum Profits Based on Predicted Returns 1965:01-2007:08

We use the past common information to predict the stock returns, then long the stocks with the highest predicted returns and short the stocks with the lowest predicted returns. Table 3 presents the results. The momentum (Winner-Loser) profits for the size portfolios are reported in Panel A, and those for the industry portfolios are reported in Panels B. Table 4 also distinguishes between January and other calendar months.

	Overall	Jan	Non-Jan
		Panel A: Size Portfolios	
	Overall	Jan	Non-Jan
Winner- loser	0.0103	0.0185	0.0095
	7.94	2.56	7.65
Winner	0.0148	0.0500	0.0115
	6.20	5.16	4.82
Loser	0.0045	0.0315	0.002
	1.80	3.01	0.79
		Panel B: Industry Portfolios	
Winner- loser	0.0074	0.0086	0.0073
	4.06	1.09	3.92
Winner	0.0147	0.06	0.0106
	6.01	5.86	4.37
Loser	0.0073	0.0514	0.0032
	2.55	4.74	1.13

We also further examine the economic significance of the long-run over-reaction since it could be true that the economic significance we document in Table 4 is mainly due to strong short-run under-reaction or $b_{i,1}$. Essentially, we repeat the above exercise except that the predicted return is now only based on the long-run over-reaction from the forecasting model Equation (5). That is $\hat{r}_{i,t} = \hat{c}_{i,2} \sum_{k=2}^{12} f_{t-k} + \hat{c}_{i,3} \sum_{k=13}^{24} f_{t-k}$. Table 5 presents the results. The momentum profits for the size portfolios are reported in Panel A, and those for the industry portfolios are reported in Panel B. Table 5 also distinguishes between January and other calendar months. Overall, momentum strategies are still significantly profitable in the two sets of portfolios. Excluding January, the average profits for the size and industry portfolio are 0.35% per month (t-statistic = 3.06), and 0.50% per month (t-statistic = 2.71), respectively. Therefore, the long-run over-reaction is also economically significant.

Table 5 Momentum Profits Based on Long-Run Overreaction 1965:01-2007:08

This table presents the momentum profits based on the long-horizon overreaction. The momentum (Winner-Loser) profits for the size portfolios are reported in Panel A, and those for the industry portfolios are reported in Panels B. Table 5 also distinguishes between January and other calendar months.

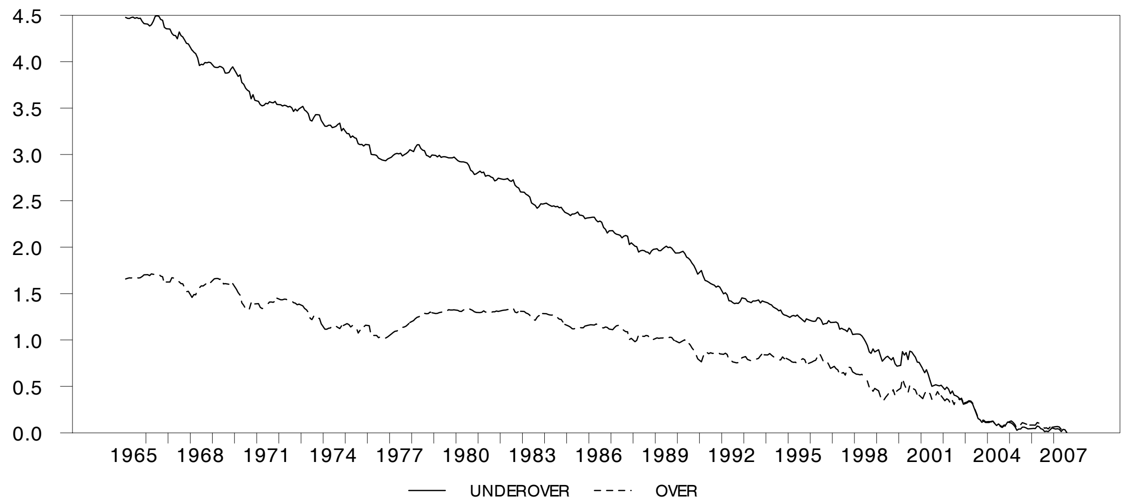
	Overall	Jan	Non-Jan
		Panel A: Size Portfolios	
	Overall	Jan	Non-Jan
Winner- loser	0.0019	-0.0155	0.0035
	1.56	-2.13	3.06
Winner	0.0105	0.0298	0.0087
	4.59	3.17	3.75
Loser	0.0085	0.0453	0.0052
	3.36	4.28	2.03
		Panel B: Industry Portfolios	
Winner- loser	0.0038	-0.0098	0.0050
	2.10	-1.41	2.71
Winner	0.0128	0.0496	0.0094
	5.52	5.33	4.05
Loser	0.009	0.0594	0.0044
	3.09	5.36	1.50

Figure 1 depicts the profits accumulated through August 2007 starting with different investment months (excluding January). The solid line represents the profits based on both short-run under-reaction and long-run over-reaction, while the dashed line represents the profits based on only long-run over-reaction. If the strategies are always profitable, the lines should slope monotonically downward. Although there are periods during which the lines are flat or even upward sloping, in most periods, the lines are downward sloping. These results suggest that the mis-reaction we document in this paper is robust for most periods and economically significant.

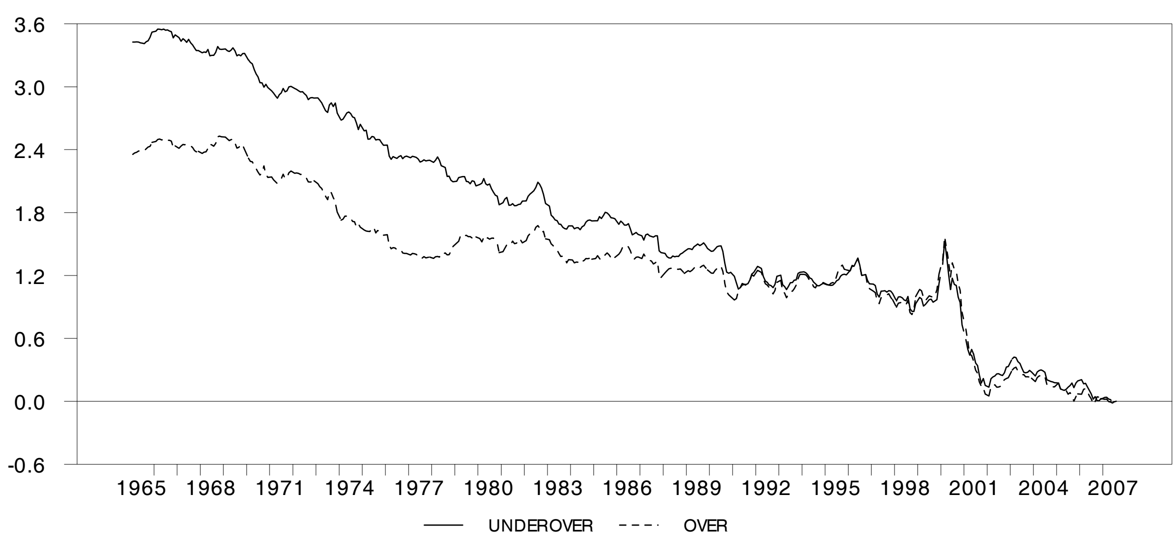
Figure 1 Cumulative Profits Given Alternative Dates of First Investing in the Strategy: 1965:01-2007:08

At the beginning of each month t, size/industry portfolios are ranked in ascending order on the basis of their predicted returns. Based on their rankings, we long in the top three portfolios (winners) and short the bottom three portfolios (losers) in an equal-weighted fashion. These positions are held for 1 month. The reported cumulative profit to entering in month *t* is $\sum_{\tau=t}^{2007:08} WML_t$, where WML_t is the momentum profit in month *t*.

Panel A: Size Portfolios



Panel B: Industry Portfolios



3.4 Market States and Delayed Reaction to Common Information

Recently, Cooper, Gutierrez, and Hameed (2004) (CGH) suggest that the behavioral models of DHS and HS imply that mis-reaction depends on the market state: mis-reaction should be stronger following UP states and weaker following DOWN states. Following an UP market, aggregate overconfidence should be stronger since investors in the aggregate hold long positions in the stock market, which should cause stronger over-reaction as DHS suggest. Alternatively, risk aversion should be weaker following an UP market due to increases in wealth, which should lead to a greater delay in over-reaction according to HS. We test this implication in this section.

Following CGH, we use the prior cumulative market returns to identify the market state. If it is non-negative (negative), we define the state of the market as “UP” (“DOWN”). We use the measurement interval of the preceding two years to match our forecasting interval. To test whether delayed reaction depends on the UP and DOWN state, we follow CGH and regress the raw momentum profits we obtained from the last section on an UP dummy and an intercept. The estimated coefficients of the UP dummy and associated Newey-West t-statistics are reported in Table 6. Interestingly, momentum strategies are not significantly more profitable following UP market states, indicative that the delayed reaction to common information is not state dependent. The cause should be interesting for a future research.

Table 6 Momentum Profits Based on Predicted Returns and Market States 1965:01-2007:08

Following CGH, we use the prior cumulative market return to identify the market state. If it is non-negative (negative), we define the state of the market as “UP” (“DOWN”). ”). We use the measurement interval of prior two years to match our forecasting interval. To test whether delayed reaction depends on UP and DOWN, we follow CGH and regress raw momentum profits we obtained from the last section on an UP dummy and an intercept. The estimated coefficients of the UP dummy and associated Newey-West t-statistics are reported in this table.

	Size Portfolios	Industry Portfolios
Winner- loser	-0.0045	-0.0011
	-0.97	-0.23
Winner	-0.0068	-0.0076
	-0.66	-0.67
Loser	-0.0023	-0.0065
	-0.29	-0.72

3.5 Tangible and Intangible Information

Daniel and Titman (2006) show that stocks react to tangible news (past performance news) and intangible news (news not related to past performance or news related to growth potential) differently: stocks react to tangible news properly, but mis-react to intangible news. In the same spirit, we decompose common information into tangible and intangible components. Kothari, Lewellen, and Warner (2006) show that aggregate earnings are most closely related to industrial production. We therefore use industrial production as a measure of the aggregate performance. We decompose the market return (the common information proxy) by using the following regression model.

$$f_t = a + bIP_{t-2} + e_t \tag{6}$$

where f_t is the market-wide information at time *t* measured by the value-weighted market return, and IP_{t-2} is the growth rate of industrial production at $t-2$. We use IP_{t-2} because the final industrial production data are usually announced with a two month delay. Unreported results show that there is a strong correlation between the market return and the 2-month lagged industrial production growth, the correlation coefficient is -0.22 with a t-statistics of -2.07. This is consistent with Kothari, Lewellen, and Warner (2006).

Following Daniel and Titman (2006), we use the fitted component of the regression as the measure of tangible news at time *t*, or the common information related to past performance of firms; we use the regression residual as the measure for intangible news, or the common information related to growth potential. We report the results for the size and industry portfolios in Tables 7 and 8. Table 7 Panel A shows how the size portfolios react to tangible common information, while Panel B presents the results for intangible common information. None of the lagged tangible common information coefficients are significant, where 19 out of 30 lagged intangible common information coefficients are significant. The results for the industry portfolios are similar. Therefore, consistent with Daniel and Titman (2006), even for common information, stocks react to tangible news properly, but mis-react to intangible news. This suggests that the delayed reaction to common information we documented in Section 3.2 is mainly due to mis-reaction to intangible common information. Not surprisingly, the $b_{i,1}$, $b_{i,2}$ and $b_{i,3}$ estimates in Tables 7 and 8, the sensitivities to intangible common information, are quite close to those reported in Tables 2 and 3 for overall common information.

Industrial production growth may not capture all tangible common information. Flannery and Protopapadakis (2002) find six macro factors that influence stock returns: three nominal (CPI, PPI, and a Monetary Aggregate) and three real (Balance of Trade, Employment Report, and Housing Starts). We use these six variables to construct the tangible and intangible common information components. The results are similar as those reported in Tables 7 and 8.[12] Thus, stock mis-reaction to common information is mainly due to mis-reaction to intangible common information, not tangible common information.

[12] The results are available upon request.

Table 7 Stock Reaction to Tangible and Intangible Common Information: Size Portfolios

We estimate the following model for each portfolio.

$$r_{i,t} = \mu_i + b_{i,0} f_t + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k=13}^{24} f_{t-k} + e_{i,t}$$

where $r_{i,t}$ is the return of asset *i* at time *t*, f_{t-k} is tangible or intangible common information at time *t* – *k*, and $b_{i,k}$ is the sensitivity of stock *i*. $b_{i,k}$ estimates are reported in the main rows, with the Newey-West test t-statistics immediately below each main row.

Industry	μ_i	$b_{i,0}$	$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$\overline{R}^2$
			Panel A Tangible Common Information			
Small 1	0.013	0.721	1.651	0.132	-0.301	0.012
	0.29	0.89	1.41	0.58	-1.32	
2	0.006	1.039	1.500	0.064	-0.218	0.010
	0.17	1.49	1.51	0.33	-1.29	
3	0.003	0.902	1.540	0.055	-0.179	0.009
	0.12	1.36	1.55	0.29	-1.30	
4	0.002	0.947	1.281	0.057	-0.157	0.008
	0.08	1.54	1.45	0.32	-1.17	
5	0.001	0.930	1.150	0.086	-0.160	0.008
	0.06	1.53	1.47	0.51	-1.34	
6	-0.003	0.837	1.298	0.064	-0.113	0.008
	-0.12	1.45	1.56	0.38	-1.00	
7	-0.001	0.923	1.295	0.071	-0.141	0.011
	-0.03	1.59	1.64	0.42	-1.30	
8	-0.002	0.924	1.211	0.071	-0.131	0.010
	-0.09	1.70	1.60	0.45	-1.37	
9	0.009	0.793	0.757	0.044	-0.152	0.006
	0.46	1.52	1.10	0.31	-1.65	
Big 10	0.005	0.604	0.550	0.044	-0.101	0.002
	0.35	1.27	0.94	0.35	-1.31	
			Panel B Intangible Common Information			
Small 1	0.014	1.113	**0.354**	-0.020	**-0.028**	0.576
	7.28	20.93	7.43	-1.63	-2.38	
2	0.011	1.216	**0.207**	**-0.019**	**-0.016**	0.733
	7.75	31.82	5.61	-1.94	-2.02	
3	0.011	1.210	**0.155**	**-0.022**	**-0.012**	0.791
	9.84	37.84	5.09	-2.85	-2.04	
4	0.011	1.186	**0.133**	**-0.016**	**-0.014**	0.812
	10.31	38.6	4.75	-2.35	-2.64	
5	0.011	1.173	**0.098**	**-0.018**	-0.009	0.84
	12.31	41.45	4.20	-3.13	-1.86	
6	0.010	1.137	**0.071**	**-0.016**	-0.009	0.866
	12.97	44.94	3.24	-2.94	-1.89	
7	0.011	1.125	**0.060**	**-0.017**	-0.007	0.903
	15.13	59.01	3.39	-3.43	-1.85	
8	0.010	1.103	0.021	**-0.017**	-0.004	0.916
	17.56	55.22	1.42	-4.83	-1.18	
9	0.01	1.028	0.000	**-0.012**	-0.001	0.929
	22.06	65.19	-0.04	-3.47	-0.60	
Big 10	0.009	0.990	-0.018	-0.002	0.004	0.942
	24.75	56.57	-1.74	-0.79	1.85	

Table 8 Stock Reaction to Tangible and Intangible Common Information: Industry Portfolios

We estimate the following model for each portfolio.

$$r_{i,t} = \mu_i + b_{i,0} f_t + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k=13}^{24} f_{t-k} + e_{i,t}$$

where $r_{i,t}$ is the return of asset *i* at time *t*, f_{t-k} is tangible or intangible common information at time *t* – *k*, and $b_{i,k}$ is the sensitivity of stock *i*. $b_{i,k}$ estimates are reported in the main rows, with the Newey-West test t-statistics immediately below each main row.

Industry	μ_i	$b_{i,0}$	$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$\overline{R}^2$
			Panel A Tangible Common Information			
NoDur	-0.021	1.277	1.206	0.207	-0.095	0.018
	-0.76	2.18	1.60	1.12	-0.74	
Durbl	-0.004	0.536	1.665	0.082	-0.127	0.005
	-0.11	0.67	1.55	0.32	-0.78	
Manuf	-0.005	0.675	1.346	0.092	-0.100	0.006
	-0.19	1.09	1.65	0.51	-0.82	
Energy	0.014	0.602	1.084	-0.04	-0.114	0.000
	0.57	0.75	1.46	-0.27	-0.83	
HiTec	0.001	0.212	**2.147**	0.066	-0.159	0.004
	0.04	0.26	2.71	0.29	-1.10	
Telcm	0.019	1.143	0.847	-0.019	-0.216	0.003
	0.63	1.50	1.04	-0.08	-1.59	
Shops	-0.025	1.521	**1.790**	0.242	-0.152	0.026
	-0.79	2.36	2.06	1.23	-1.03	
Hlth	-0.025	1.452	**1.715**	0.247	-0.131	0.016
	-0.93	2.05	2.20	1.45	-0.91	
Utils	0.021	1.018	0.266	0.036	-0.221	0.014
	0.66	1.72	0.30	0.29	-1.49	
Other	0.014	0.918	1.083	0.093	-0.263	0.013
	0.44	1.44	1.14	0.43	-1.67	
			Panel B Intangible Common Information			
NoDur	0.010	0.929	**0.195**	**-0.022**	**-0.025**	0.692
	7.69	22.99	7.36	-2.51	-3.43	
Durbl	0.010	1.185	**0.241**	-0.018	**-0.02**	0.685
	6.23	24.49	6.47	-1.68	-1.98	
Manuf	0.012	1.103	**0.180**	**-0.019**	**-0.014**	0.767
	9.90	30.59	6.42	-2.33	-1.98	
Energy	0.013	1.038	0.022	-0.001	-0.008	0.446
	5.18	16.34	0.47	-0.07	-0.62	
HiTec	0.011	1.475	**0.233**	**-0.027**	-0.019	0.668
	6.03	22.93	5.69	-2.26	-1.81	
Telcm	0.012	1.231	**0.201**	**-0.027**	-0.014	0.626
	6.40	19.15	5.07	-2.24	-1.35	
Shops	0.011	1.038	**0.256**	-0.022	**-0.024**	0.680
	6.46	26.05	8.23	-1.79	-2.70	
Hlth	0.013	1.195	**0.180**	**-0.032**	-0.019	0.630
	6.68	34.88	4.92	-2.56	-1.84	
Utils	0.012	0.594	0.009	-0.001	0.004	0.415
	9.03	11.49	0.26	-0.19	0.55	
Other	0.012	1.032	**0.218**	**-0.019**	**-0.019**	0.703
	8.16	21.53	6.69	-2.04	-2.52	

3.6 Fama-French Size and BM factors and Delayed Reaction to Common Information

Vassalou (2003) finds that the Fama-French size and BM factors contain information about future economic growth.[13] We find that stocks mis-react to such intangible common information. This observation thus motivates us to investigate whether the Fama-French size and BM factors also proxy the delayed reaction to such intangible common information. If so, we provide a complementary explanation for these two factors. Toward this end, we consider the following regression model:

$$r_{i,t} = \mu_i + b_{i,0} f_t + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k=13}^{24} f_{t-k} + b_{i,4} FF_t + e_{i,t} \tag{7}$$

where FF is either the size factor (SMB) or the BM factor (HML). If they do proxy delayed reaction, the lagged common information will lose their explanatory power.

The results for two sets of US portfolios are reported in Tables 9 and 10. Panel As present the results for the size factor, while Panel Bs present the results for the BM factor. $b_{i,k}$ estimates and associated Newey-West t-statistics are reported. The values reported in the main rows are the actual values of $b_{i,k}$ estimates, and the entries below are the Newey-West test statistics. When the size factor is added, the lagged market returns generally become either insignificant or less significant. Compare Panel A of Table 9 to Table 2, the number of the significant lagged common-factor coefficients (i.e. $b_{i,k}$ for k = 1, 2 and 3) for the size-sorted portfolios decrease from 22 out of 30 to 5 out of 30. Even the remaining five significant coefficients become less significant. For instance, for the smallest decile portfolio, $b_{1,1}$ decreases from 0.342 with a t-statistic of 7.39 to 0.168 with a t-statistic of 3.61. Similar patterns are also found in Panel A of Table 10 for the industry portfolios. The number of significant lagged common-factor coefficients for the industry portfolios decreases from 20 out of 30 to 9 out of 30. Similarly, the remaining significant coefficients also become less significant. Therefore, the evidence seems to suggest that the Fama-French size factor to some extent also proxies the delayed reaction to intangible common information.

However, adding the BM factor seems to have little impact. For instance, compare Panel B of Table 9 to Table 2, the results for the size portfolios are almost identical with or without the BM factor. There are still 24 coefficients of the lagged common information variables that are significant. Furthermore, their significance is almost identical to that without the BM factor. Similar patterns are also found for the industry portfolios. Therefore, the Fama-French BM factor seems to be unrelated to the stock delayed reaction to intangible common information.

[13] See also Li, Vassalou, and Xing (2006) among others.

Table 9 Delayed Reaction and Fama-French Size and BM Factors: Size-Sorted Portfolios

We estimate the following model for each portfolio.

$$r_{i,t} = \mu_i + b_{i,0} f_t + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k=13}^{24} f_{t-k} + b_{i,4} FF_t + e_{i,t}$$

where $r_{i,t}$ is the return of asset *i* at time *t*, f_{t-k} is the market-wide information at time *t* – *k* measured by the value-weighted market return, FF is either the size factor or the book-to-market factor, and $b_{i,k}$ is the sensitivity of stock *i*. $b_{i,k}$ estimates are reported in the main rows, with the Newey-West test t-statistics immediately below each main row.

Size	μ_i	$b_{i,0}$	$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$b_{i,4}$	$\overline{R}^2$
			Panel A: FF = the size factor				
Small 1	0.006	0.889	**0.168**	-0.006	**-0.018**	1.235	0.763
	2.93	25.44	3.61	-0.72	-2.48	8.57	
2	0.000	1.034	0.059	-0.002	-0.006	1.017	0.918
	0.21	49.27	1.82	-0.35	-1.41	9.87	
3	0.001	1.047	0.028	-0.006	-0.004	0.859	0.946
	1.29	60.95	1.07	-1.62	-1.23	8.46	
4	0.000	1.042	0.016	-0.001	-0.005	0.779	0.947
	0.51	53.16	0.68	-0.31	-1.88	8.05	
5	0.001	1.051	0.002	-0.005	-0.002	0.647	0.943
	1.42	52.55	0.10	-1.74	-0.83	7.09	
6	0.001	1.050	0.003	-0.005	-0.003	0.466	0.929
	1.37	55.19	0.12	-1.40	-1.06	4.63	
7	0.001	1.066	0.013	**-0.008**	-0.004	0.320	0.937
	2.21	61.18	0.62	-2.39	-1.41	3.69	
8	0.001	1.066	-0.008	**-0.010**	-0.002	0.202	0.935
	1.98	54.72	-0.46	-3.80	-0.83	2.92	
9	0.001	1.023	-0.005	**-0.008**	-0.002	0.033	0.935
	2.82	74.2	-0.37	-2.73	-0.76	0.53	
Big 10	-0.001	1.031	0.011	-0.002	0.001	-0.222	0.966
	-1.61	72.19	1.04	-0.90	0.53	-5.77	
			Panel B: FF = the BM factor				
Small 1	0.004	1.190	**0.332**	**-0.023**	**-0.032**	0.464	0.570
	1.56	20.67	7.51	-1.96	-2.83	2.33	
2	0.000	1.259	**0.198**	-0.016	**-0.018**	0.237	0.738
	0.00	31.20	5.78	-1.76	-2.38	1.89	
3	0.001	1.230	**0.146**	**-0.018**	**-0.014**	0.154	0.797
	0.73	40.10	5.14	-2.60	-2.47	1.97	
4	0.001	1.203	**0.124**	-0.012	**-0.015**	0.107	0.814
	0.46	40.96	4.70	-1.85	-2.93	1.40	
5	0.001	1.183	**0.092**	**-0.014**	**-0.011**	0.079	0.844
	0.91	46.13	4.13	-2.62	-2.22	1.16	
6	0.001	1.154	**0.066**	**-0.011**	**-0.009**	0.114	0.875
	0.61	52.25	3.22	-2.34	-2.11	2.38	
7	0.001	1.143	**0.055**	**-0.013**	**-0.007**	0.118	0.912
	1.16	63.85	3.44	-2.77	-2.27	3.50	
8	0.001	1.120	0.018	**-0.013**	-0.004	0.110	0.926
	1.16	60.70	1.46	-4.17	-1.45	3.67	
9	0.001	1.047	-0.003	**-0.009**	-0.001	0.117	0.939
	1.46	75.26	-0.47	-3.08	-0.71	3.31	
Big 10	-0.001	0.995	**-0.021**	0.001	**0.004**	0.029	0.947
	-1.83	67.28	-2.23	0.47	2.20	0.51	

Table 10 Delayed Reaction and Fama-French Size and BM Factors: Industry Portfolios

We estimate the following model for each portfolio.

$$r_{i,t} = \mu_i + b_{i,0} f_t + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k=13}^{24} f_{t-k} + b_{i,4} FF_t + e_{i,t}$$

where $r_{i,t}$ is the return of asset *i* at time *t*, f_{t-k} is the market-wide information at time *t* – *k* measured by the value-weighted market return, FF is either the size factor or the book-to-market factor, and $b_{i,k}$ is the sensitivity of stock *i*. $b_{i,k}$ estimates are reported in the main rows, with the Newey-West test t-statistics immediately below each main row.

Industry	μ_i	$b_{i,0}$	$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$b_{i,4}$	$\overline{R}^2$
Panel A: FF = the size factor							
NoDur	0.004	0.808	**0.098**	-0.008	**-0.017**	0.683	0.838
	2.99	29.37	2.90	-1.33	-3.10	4.95	
Durbl	0.000	1.015	**0.105**	-0.001	-0.010	0.901	0.830
	-0.26	29.47	2.37	-0.14	-1.40	5.52	
Manuf	0.001	0.971	**0.076**	-0.003	-0.005	0.704	0.890
	1.29	37.68	2.31	-0.55	-1.04	5.69	
Energy	0.004	0.959	-0.040	0.005	-0.003	0.437	0.482
	1.50	16.47	-0.81	0.38	-0.30	3.06	
HiTec	-0.001	1.226	0.044	-0.007	-0.005	1.254	0.855
	-0.42	22.22	1.33	-0.84	-0.65	20.77	
Telcm	0.002	1.088	**0.092**	-0.014	-0.006	0.753	0.719
	0.58	18.77	2.95	-1.16	-0.59	12.92	
Shops	0.002	0.894	**0.145**	-0.005	**-0.014**	0.810	0.842
	1.32	31.75	3.67	-0.55	-2.13	5.44	
Hlth	0.004	1.018	0.046	-0.013	-0.009	0.921	0.781
	2.1	29.85	1.91	-1.33	-1.11	10.3	
Utils	0.004	0.622	0.008	0.005	0.006	0.059	0.410
	1.88	13.06	0.24	0.61	0.75	0.57	
Other	0.004	0.900	**0.104**	-0.008	**-0.014**	0.730	0.800
	2.87	26.7	2.87	-1.18	-2.45	4.79	
Panel B: FF = the BM factor							
NoDur	0.003	0.980	**0.188**	**-0.018**	**-0.024**	0.287	0.726
	1.60	28.16	7.31	-2.28	-3.70	5.38	
Durbl	-0.001	1.235	**0.225**	-0.014	**-0.021**	0.343	0.704
	-0.64	29.58	6.37	-1.47	-2.24	4.30	
Manuf	0.001	1.145	**0.169**	-0.013	**-0.013**	0.283	0.791
	0.37	39.66	6.43	-1.84	-2.04	5.67	
Energy	0.002	1.106	0.012	-0.002	-0.007	0.428	0.482
	0.77	20.4	0.26	-0.13	-0.55	4.71	
HiTec	0.003	1.392	**0.230**	**-0.023**	**-0.024**	-0.427	0.689
	1.20	27.61	5.41	-1.98	-2.32	-2.33	
Telcm	0.004	1.19	**0.204**	**-0.023**	-0.017	-0.245	0.639
	1.65	26.32	5.01	-2.17	-1.72	-1.48	
Shops	0.002	1.066	**0.256**	-0.016	**-0.024**	0.140	0.697
	0.93	27.99	8.60	-1.37	-2.84	2.14	
Hlth	0.008	1.128	**0.185**	**-0.024**	**-0.024**	-0.394	0.663
	3.00	26.56	4.98	-2.06	-2.37	-3.24	
Utils	0.001	0.719	0.004	0.003	0.008	0.559	0.541
	0.33	14.12	0.15	0.35	1.15	5.65	
Other	0.002	1.117	**0.195**	**-0.019**	**-0.02**	0.527	0.742
	1.02	28.84	6.46	-2.30	-2.83	6.07	

To confirm our findings, we directly test the relationship between the delayed reaction and the Fama-French size and BM factors with the following regression model.

$$FF_t = \mu_i + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k=13}^{24} f_{t-k} + e_{i,t} \tag{8}$$

where FF_t is either the size factor or the book-to-market factor at time *t*, and f_{t-k} is the market-wide information at time *t* – *k* measured by the value-weighted market return. The results are reported in Table 11. $b_{i,k}$ estimates are reported in the main rows, with the Newey-West test t-statistics immediately below each main row. As we expected, only the size factor proxies the delayed reaction to common information in the sense that the coefficients of the lagged common information variable are significant. The BM factor is not related to the delayed reaction. Thus, our results suggest that the size factor may not only proxy future economic growth as Vassalou (2003) argues, but also the delayed reaction to such news related to future economic growth.

Table 11 Delayed Reaction and Fama-French Size and BM Factors

We estimate the following model for the Fama-French size and BM factors.

$$r_{i,t} = \mu_i + b_{i,1} f_{t-1} + b_{i,2} \sum_{k=2}^{12} f_{t-k} + b_{i,3} \sum_{k=13}^{24} f_{t-k} + e_{i,t}$$

where $r_{i,t}$ is either the size factor or the book-to-market factor at time *t*, and f_{t-k} is the market-wide information at time *t* – *k* measured by the value-weighted market return. $b_{i,k}$ estimates are reported in the main rows, with the Newey-West test t-statistics immediately below each main row.

	μ_i	$b_{i,1}$	$b_{i,2}$	$b_{i,3}$	$\overline{R}^2$
Size Factor	0.003	**0.154**	**-0.014**	**-0.016**	0.061
	2.25	5.59	-2.12	-2.76	
BM Factor	0.004	0.012	0.002	-0.004	-0.003
	3.18	0.51	0.35	-0.60	

4. Conclusion

An anomaly within the behavioral literature is that, to date, there is as yet no evidence suggesting that stocks also mis-react to common information as they do to firm-specific information. For instance, Kothari, Lewellen, and Warner (2006) recently find that market level returns neither under- nor over-react to common information. We ague in this paper that even if stocks under- and/or over-react to common information at the security level, the reaction pattern may not be evident at the market level if only some stocks have such a pattern and their capitalization is small. We thus examine stock reaction to common information at the stock level in this paper. We find a statistically and economically significant reaction pattern to common information as the behavioral models suggest. This finding complements the findings of stock mis-reaction to firm-specific information, and thus should benefit researchers attempting to understand investor behavior. Furthermore, we find that the Fama-French size factor seems to proxy this delayed reaction to common information, and that the delayed reaction to common information is mainly due to mis-reaction to intangible common information. Considered together, our results supplement Vassalou (2003) and suggest that the size factor may not only proxy future economic growth, but also the delayed reaction to the news related to future economic growth. This paper therefore also contributes the literature by advancing an understanding of the size factor.

Appendix

Based on the return-generating model in Equation (1a), we can easily see the implication of Lo and MacKinlay (1990), Jegadeesh and Titman (1995), and Lewellen (2002). The cross-serial covariance between the return of *i* and *j* is

$$\mathrm{cov}(r_{i,t}, r_{j,t-n}) = \sum_{k=n}^{K} b_{i,k} b_{j,k-n} \sigma_f^2 \tag{9}$$

where $E(f_t^{\,2}) = \sigma_f^2$. Consequently, using this model, the stock price reaction to the common factor entirely determines the cross-serial correlation between stocks.[14] As the behavioral models suggest, some stock returns, *i*, under- and over-react to information ($b_{i,k} \neq 0 \ \mathit{for\ all}\ k \neq 0$), while some other stocks, *j*, do not ($b_{j,k} = 0 \ \mathit{for\ all}\ k \neq 0$). So

$\mathrm{cov}(r_{i,t}, r_{j,t-n}) = \sum_{k=n}^{K} b_{i,k} b_{j,k-n} \sigma_f^2 = b_{i,n} b_{j,0} \sigma_f^2$ and $\mathrm{cov}(r_{j,t}, r_{i,t-n}) = \sum_{k=n}^{K} b_{j,k} b_{i,k-n} \sigma_f^2 = 0$ for $n = 1, \ldots, K$. Since $b_{j,0}\sigma_f^2 > 0$, $\mathit{sign}[\mathrm{cov}(r_{i,t}, r_{j,t-n})] = \mathit{sign}(b_{i,n})$. One thus may infer stock under- or over-reaction to the common factor from cross-serial correlations between stock returns. For example, if $\mathrm{cov}(r_{i,t}, r_{j,t-1}) > 0$ but $\mathrm{cov}(r_{j,t}, r_{i,t-1}) = 0$, (*j* leads *i* since *j*'s return predicts *i*'s return but the reverse is not true), this implies that $b_{i,1} > 0$ and $b_{j,1} = 0$ (stock *i* under-reacts to the common factor in the short run but stock *j* does not). Thus, the short-run lead-lag evidence in Lo and MacKinlay (1990) is consistent with the short-run under-reaction of some stocks to the common information.[15] On the other hand, if $\mathrm{cov}(r_{i,t}, r_{j,t-n}) < 0$ but $\mathrm{cov}(r_{j,t}, r_{i,t-n}) = 0$ for $n = 1, \ldots, K$ (*j* again leads *i*), then it implies that $b_{i,k} < 0 \ \mathit{for\ all}\ k \neq 0$ and $b_{j,k} = 0 \ \mathit{for\ all}\ k \neq 0$ (stock *i* over-reacts to the common factor but stock *j* does not). Hence, the negative average of cross-serial correlations across lags from 1 to 30 in Lewellen (2002) may suggest over-reaction at all horizons.

However, it is important to note that if stocks under-react in the short run, $b_{i,k} > 0$ for some small *k*, and over-react in the long run $b_{i,k} < 0$ for some large *k* as suggested by the behavioral models, calculating the average of cross-serial correlations for lags from 1 to 30 as in Lewellen (2002), is not appropriate. First, an average of cross-serial correlations may mask different cross-serial correlations at different horizons. Thus, the evidence in Lewellen (2002)

[14] It is easy to see that it also determines in part the serial autocorrelation of stock returns.
[15] This is consistent with the results of Jegadeesh and Titman (1995).

may not necessarily imply a rejection of the recent behavioral models. Secondly, the test may have little power because positive cross-serial covariances at short horizons will offset negative cross-serial covariances at longer horizons.

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