Endogenous Information, Risk Characterization, and the Predictability of Average Stock Returns

(Informação Endógena, Caracterização do Risco e Retornos de Ações Variantes no Tempo)

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Abstract

In this paper we provide a new type of risk characterization of the predictability of two widely known abnormal patterns in average stock returns: momentum and reversal. The purpose is to illustrate the relative importance of common risk factors and endogenous information. Our results demonstrate that in the presence of zero-investment factors, spreads in average momentum and reversal returns correspond to spreads in the slopes of the endogenous information. The empirical findings support the view that various classes of firms react differently to volatility risk, and endogenous information harbor an important sources of potential risk loadings. Taken together, our results suggest that the stock returns are influenced by random endogenous information flow, which is asymmetric in nature, and can be used as a performance attribution factor. If one fails to incorporate the existing asymmetric endogenous information hidden in the historical behavior, any attempt to explore average stock return predictability will be subject to an unquantified specification bias.

***Keywords*:** stock returns; volatility persistence; endogenous information; momentum; reversal.

JEL codes: G1; G12; G14; G15.

Resumo

Neste artigo, oferecemos um novo tipo de caracterização do risco da previsibilidade de dois conhecidos padrões anormais dos retornos médios das ações: momento e reversões. O objetivo é ilustrar a importância relativa dos fatores comuns de risco e da informação endógena para explicar a variabilidade no tempo dos retornos de momento e reversão. Nossos resultados demonstram que, mesmo na presença de carteiras de investimento nulo, os *spreads* dos retornos médios de momento e reversão correspondem aos *spreads* dos coeficientes angulares da informação endógena. Os resultados empíricos corroboram a perspectiva de que várias classes de empresas reagem de forma diferente ao risco de volatilidade e, tanto o tamanho quanto a relação valor patrimonial – valor de mercado da ação médios das empresas, contém, em conjunto, importantes fontes de risco potencial. Tomados em conjunto, nossos resultados sugerem que os retornos são influenciados pelo fluxo endógeno

Submitted 3 June 2011. Reformulated 1 February 2012. Accepted 22 June 2012. Published online 15 October 2012. The article was double blind refereed and evaluated by the editor. Supervising editor: Ricardo P. C. Leal.

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de informações aleatórias, que é assimétrico por natureza e que pode ser usado como fator de atribuição de desempenho. Quando não se incorporam as informações endógenas assimétricas existentes, escondidas no comportamento histórico, qualquer tentativa de explorar a previsibilidade da média do retorno das ações estará sujeita a um viés de especificação não quantificado.

***Palavras-chave*:** retornos de ações; persistência da volatilidade; informação endógena; momento; reversão.

1. Introduction

In this paper we study two of the most prominent stock market anomalies concurrently. They are – continuation of short-term returns (or momentum returns) and reversal of long-term returns (or contrarian returns).[1] Several studies have presented strong empirical evidence that abnormal profits of momentum and reversal strategies exists in the US and non-US equity markets.[2] The broad appeal of momentum strategy against market efficiency has lead to a huge literature on the relative importance of common versus firm specific sources of momentum payoffs (see e.g., Asness *et al.* (2010), and Ammann *et al.* (2011), Fama & French (2008), Liu & Zhang (2008), and Novy-Marx (2012)). Despite their popularity, the cause of momentum and reversal are far from unambiguous and is a matter of intense academic debate.[3]

Our objective in this paper is to provide a new type of risk characterization of the predictability of these two widely known abnormal patterns in average stock returns. We show that, contrary to the standard paradigm, once we take into account a scaled version of unaccounted information as a priced risk factor, we can explain a significant amount of momentum and reversal returns not recognized in the existing literature. Since the scaled information is hidden in the stock returns' historical behavior we term it as endogenous information.

To explain the time-series variability of momentum and reversal returns, we

[1]The attractiveness of these two portfolio strategy depends on their relatively simple trading rules. The momentum strategy is based on price continuations and the contrarian strategy is based on price reversals. Under the momentum strategy, past winners are bought and past losers are shorted or sold. For the contrarian strategy, past losers are bought and past winners are shorted or sold.

[2]For example, DeBondt & Thaler (1985, 1987) investigate return patterns over an extended period of time and find that contrarian strategies perform well over a 3-5 year horizon. They show that from 1926 to 1982, 'loser' portfolios outperformed the market by 19.6% after 36 months, while 'winner' portfolios earned 5% less than the market over the same time period. Jegadeesh & Titman (1993, 1995, 2001) document return continuations in intermediate horizons over 3-12 month holding periods where on average past winners continue to outperform past losers. This evidence has been extended to stocks in other countries (Fama & French, 1998, Rouwenhorst, 1998), industry-level portfolios (Grinblatt & Moskowitz, 1999), country indices (Asness *et al.*, 1997, Bhojraj & Swaminathan, 2006), bonds (Asness *et al.*, 2010), currencies (Bhojraj & Swaminathan, 2006) and commodities (Gorton *et al.*, 2007). Asness *et al.* (2010) extend and unify much of this evidence and contain additional references.

[3]The traditional rational argument believes that momentum profits are a compensation for systematic risks. There is an emerging literature which suggests that one possible explanation of these anomalies is behavioral. See, for example, Barberis *et al.* (1998), Daniel *et al.* (1998), Hong & Stein (1999), and Barberis & Shleifer (2003).

examine the relative importance of common risk factors that are related to firm size (ME) and book-to-market equity (BE/ME), and elements of endogenous information associated with past returns based portfolios. Though the value of scaled information is not unique for individual money managers, it can be related to the evidence of systematic risk. Our interpretation is that endogenous information get entrapped in the historical behavior of stock returns, acts like a potential state variable, and captures the variability of average stock returns. One important contribution of this paper is that we are able to demonstrate that the risk associated with this endogenous information is separate from either market or value-growth risk, and is compensated differently in expected returns.

Following Fama & French (1996), our presentation assumes three stock-market factors: an overall market factor, and two factors related to firm size and BE/ME.[4] More specifically, we show that when the portfolios are constructed to mimic risk factors related to size and BE/ME, they still capture strong common variation in momentum and reversal of stock returns, even when the underlying asset pricing model is intrinsically conditionally heteroskedastic. Although researchers have made considerable amount of progress in identifying various conditionally heteroskedastic asset pricing models that have better explanatory powers (e.g., see French *et al.* (1987), Bollerslev *et al.* (1988), and Jagannathan & Wang (1996)), for some reason there is absolutely no work on the role and characterization of underlying volatility dynamics in explaining average-return anomalies. Our approach is one of the first steps in that direction.

For our empirical analysis, we use the excess return of portfolios formed on past returns of all NYSE stocks on the monthly CRSP files between July 1965 and June 2007. We utilize equal-weighted portfolios formed monthly on short-term and long-term past returns of all NYSE firms. Our empirical results suggest that while common risk factors fail to capture the expected momentum returns, the elements of endogenous information do not miss the continuation of momentum returns. For average stock returns based on long-term past performance, the role of common risk factors are robust even in the joint presence of strong volatility persistence and endogenous information. Interesting aspects of our results are that various classes of firms react differently to volatility risk, and both the average size and BE/ME equity of firms jointly harbor important sources of potential risk loadings even under the presence of strong volatility persistence.

Throughout the paper we examine the effect of volatility persistence through various parsimonious model specifications. We investigate the relationship between common risk factors and stock return variability by using generalized autoregressive conditional heteroskedastic (GARCH) model.[5] We test if the exis-

[4]As Durack *et al.* (2004) noted the Fama-French three factor model has succeeded CAPM as the paradigm within which asset prices are analyzed. Therefore, it is critical to study if the support for three factor model is sensitive to model specification when we want to justify its explanatory power for the continuation of short-term returns and reversal of long-term returns.

[5]The choice of GARCH against any other higher order specifications is based on the value of the lowest Akaike Information Criterion (AIC). We also use maximum log-likelihood value and Schwartz

tence of volatility persistence can alter explanatory power of various multifactor models for the continuations of short-term and reversal of long-term returns. The persistence of volatility predicted by our model is similar to those that can be estimated by more complex GARCH procedures. Our study is unique in some important aspects. First, it provides a more realistic measure of market betas and common risk factors for momentum and reversal based portfolios when the underlying conditional variance is not constant over time, and is predicted by past forecast errors. Second, by not employing an arbitrary exogenous variable to explain heteroskedasticity, it captures some of the effects of omitted variables and non-normality problems of the regression disturbance term.

There can be many explanations behind the proxy for state variables that may describe time variation in average stock returns. What we provide is a reasonably simple but adequate story based on innovations in state variables that forecast expected stock returns. Our methodology can be seen as useful tool in empirical evaluation of multifactor asset pricing model. It can assist in making portfolio management decisions and provide added value to practitioners and retail investors alike.

In the following section we first describe the data set and methodology used throughout the paper. In section 3 we present the main empirical findings in three parts. First we outline our basic models of performance measurement. In the second part, we describe the empirical results by comparing various momentum and reversal portfolios. In the third subsection, we summarize the pervasive role of endogenous information. In section 4, we provide direct evidence on robustness checks. These include an evaluation of sub-period regression and rolling window estimates, and in-sample and out-of-sample forecasts comparisons. The final section concludes the paper.

2. Data and Methodology

For portfolio returns based on past performance we follow Chordia & Shivakumar (2002) and Liu & Zhang (2008). The average stock returns based on past performance are the return on each of the 10 decile portfolios from July 1965 through June 2007.[6] For the set of dependent variable, we utilize the sets of portfolios formed on two types of past returns of all NYSE stocks listed on the monthly CRSP files – short-run (11 months) and long-term (up to five years of). Similar to Fama & French (1996), our portfolios are formed monthly, and equal-weight simple returns in excess of the one-month bill rate are calculated for each month. That is, all 10 equal-weighted portfolios formed monthly on short term ($t-12$ to $t-2$) and long-term ($t-60$ to $t-13$) past returns of all NYSE firms.[7] At the beginning

Information Criterion (SIC) of model selection. Our final results are not sensitive to alternative specification and conditional variance.

[6] It's the maximum attainable sample period during the time this paper was written.

[7] Unlike Chordia & Shivakumar (2002) and other related studies that utilizes both NYSE and Amex firms, we use only NYSE stocks in order to avoid the influence of small stocks in the equally weighted

of each month firms with returns for month $t - x$ and $t - y$ for all NYSE firms are allocated to deciles based on their continually compounded returns between $t - x$ and $t - y$. Therefore, decile 1 momentum (reversal) portfolios contains the NYSE stocks with the lowest (highest) continuously compounded past returns, and decile 10 contains the NYSE stocks with the highest (lowest) continuously compounded past returns. Following Liu & Zhang (2008) we exclude closed end funds, real estate investment trust, American depository receipts, and foreign stocks. Among other variables, we use the return of CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks as the market return, and 1-month T-bill rate obtained from Ibbotson and Associates as the risk-free rate.

We follow Fama & French (1993) to utilize mimicking risk factors which are returns relating to size and BE/ME and are based on the intersection of 2 ME and 3 BE/ME groups. The returns on all the portfolios formed on size and BE/ME equity are obtained from Ken French.[8] All of our results are based on the period from July 1965 to June 2007. The risk factor in returns mimicking size is the difference, each month, between average returns on the 3 small stock portfolios and the average of the 3 big stock portfolios (SMB). The risk factor in returns mimicking BE/ME is the difference, each month, between the average of the returns on the two high-BE/ME portfolios and 2 low-BE/ME portfolios (HML). We also construct two other explanatory variables based on the zero-investment portfolio of momentum and reversal returns. They are – average portfolio return constructed by subtracting short-term losers from winners at each time period (WML^{SR}), and average portfolio return constructed by subtracting long-term losers from winners at each time period (WML^{LR}).

3. Empirical Specification and Results

3.1 Basic models

For empirical specification we employ the following models of performance measurement: a market model, a 3-factor (3F) model of Fama & French (1993), and a 4-factor (4F) model of Carhart (1997). They are given by (1), (2), and (3) respectively

$$r_{it} = b_{i0} + b_{i1} Mkt_t + \epsilon_{it}, \quad e_{it} | \prod_{t-1} \sim (0, \sigma^2), t = 1, ...T \tag{1}$$

$$\begin{aligned} r_{it} &= b_{i0} + b_{i1} Mkt_t + b_{i2} HML_t + b_{i3} SMB_t \\ &+ \epsilon_{it} \epsilon_{it} | \prod_{t-1} \sim (0, \sigma^2), t = 1, ...T \end{aligned} \tag{2}$$

and

portfolios across 10 deciles.

[8] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.`

$$\begin{aligned} r_{it} &= b_{i0} + b_{i1}Mkt_t + b_{i2}HML_t + b_{i3}SMB_t + b_{i4}WML_t \\ &+ \epsilon_{it}\epsilon_{it}|\prod_{t-1} \sim (0, \sigma^2), t = 1, ...T \end{aligned} \tag{3}$$

where r_{it} is the excess return on a portfolio in excess of the T-bill rate; Mkt_t is the excess market return; SMB_t and HML_t are value weighted returns on factor mimicking portfolios for size and book-to-market; WML_t is zero-investment portfolio returns based on past performances as explained in the previous section, and $\prod_{t-1}$ is the information set available at time $t-1$. A common feature is that all three basic models are conditionally homoscedastic. In order to motivate the empirical tests of this paper, we estimate model (1) through (3) for various momentum and reversal portfolio return series. Thus, the basic specification of the market and 3F model, given by (1) and (2), provides a benchmark of our analysis. The choice of specification (3) is motivated by 3F models inability to explain time-series variability of momentum returns.

In addition to simple multifactor model, we also implement a conditionally heteroskedastic version of (1) through (3); enabling us to compare the intermediate results.[9] For a parsimonious representation of conditional heteroskedastic model, first we restrict our attention to a simple GARCH(1,1) specification:

$$\epsilon_{it}|\prod_{t-1} \sim (0, V_{it}), V_{it} = \beta_{i0} + \beta_{i1}\epsilon^2_{it-1}, t = 1, ...T \tag{4}$$

where V_{it} is the conditional variance of e_{it} with respect to the information set $\prod_(t-1)$. In (4), the time-varying conditional variance not only becomes a function of the shock from last period but also of the prior period variance. As it is well known, when the sum of two slope coefficients becomes close to one, past shocks do not dissipate and persists for very long periods of time (Bollerslev *et al.*, 1988). Finally, we utilize an extended version of the specification (4), given by the following

$$\begin{aligned} \epsilon_{it}|\prod_{t-1} \sim (0, V_{it}), V_{it} &= \beta_{i0} + \beta_{i1}\epsilon^2_{it-1} + \beta_{i2}V_{it-1} + \beta_{i3}PI_{it-1} \\ &+ \beta_{i4}NI_{it-1}, t = 1, ...T \end{aligned} \tag{5}$$

where $PI_{it-1} = 1_{[r_{it-1}>0]}$ and $NI_{it-1} = 1_{[r_{it-1}<0]}$ are the endogenous information contained in the data, and $1_{[g>0]}$ is an indicator function, i.e., $1_{[g>0]} = 1$ if g is positive and zero otherwise. In the model (5), we choose positive and negative information from previous periods and utilize them in the generalized variance

[9] For practical purpose, we also use lagged values of the common risk factors and value weighted zero-investment portfolio returns in a conditionally heteroskedastic model. The inclusion of these variables does not alter our fundamental conclusions.

specification.[10] We use the assumption that endogenous information is a mixing variable; so they are also weakly exogenous in the sense of Engle *et al.* (1982), and both have additive effects on conditional variance. Following Lamoureux & Lastrapes (1990), one can argue that they are likely to contain a scaled version of unaccounted information about the disequilibrium dynamics of asset markets.[11] The estimate of slope coefficients of PI_{it-1} and NI_{it-1} helps us to disentangle the effect (if any) of such positive and negative scaled information hidden in the historical behavior of stock returns.

Note that, even though other popular versions of GARCH model (such as GARCH in mean and nonlinear GARCH etc.) provide a richer specification, the inclusion of them in our data hardly improves the forecasting performance; so we do not lose any economic content by restricting ourselves with specification (5). Heuristically, our specification is close to various asymmetric volatility models that are well established in the financial econometrics literature. The example includes Exponential GARCH (EGARCH) introduced by Nelson (1991), and GJR-GARCH proposed by Glosten *et al.* (1993). These two models, which are very popular in the literature, can be given expressed the following (ignoring subscript i):

$$EGARCH(1,1) = \ln(V_t) = \alpha + \delta \ln(V_{t-1}) + \theta[|z_{t-1}| - E(|z_{t-1}|)] + \gamma z_{t-1}$$

$$GJR - GARCH(1,1) : V_t = \alpha + \delta V_{t-1} + \theta S_{t-1}\epsilon_{t-1}^2 + \gamma e_{t-1}^2$$

where $z_{t-1} = e_{t-1}/\sqrt{V_{t-1}}$, and $S_{t-1} = 1$ if $\epsilon_{t-1} < 0$ and 0 otherwise. For GJR specification, if the leverage coefficient $\theta \neq 0$, the negative shocks have a bigger impact on future volatility than positive shocks of the same magnitude.[12]

Note that, in our case, in some way we utilize a hybrid version of these asymmetric volatility models. In the specification (5), the dummy variable keeps track not whether the lagged residual error is positive or negative, but if the lagged portfolio return is positive or negative. If the coefficient $\beta_{i3}(or \beta_{i4})$ is significant, the implication is the presence of asymmetric information spillover effect. Also, unlike GJR specification, the leverage coefficients are applied to not only negative information, but also to positive information coming from lagged portfolio

[10] We also redefined the dummy variable as equal to one if the realized return on security i is higher or lower than its average level, and zero otherwise, i.e., $PI_{it-1} = 1_{[r_{it-1} > r_t]}$ and $NI_{it-1} = 1_{[r_{it-1} < r_t]}$. The results are very similar to those reported in the paper.

[11] The idea of empirical tests based on the variance of speculative assets returns conditional on the knowledge of mixing variable is not new. For example, Mandelbrot & Taylor (1967) and Mandelbrot (1973) present an earlier discussion on this issue.

[12] Some recent references where the asymmetric relationship between return innovations and volatility is documented are Bollerslev & Zhou (2006), Eraker *et al.* (2003), Fu (2009), and Rodriguez & Ruiz (2012).

returns, giving positive changes additional weight. The consequence is that our specification (5) allows V_{it} to responds asymmetrically to positive and negative information, and there are non-negativity constraints of the GARCH parameters. In other words, PI_{it-1} and NI_{it-1} simply help to reveal the asymmetric response of the volatility to both negative and positive information of momentum and reversal returns. The coefficients of the time varying conditional variance on the other hand, measure both the 'reactiveness' and persistence of volatility to shocks. In the next subsections we describe our main empirical results and relate them to the above discussion.

3.2 Estimation results and implications

We start with Table 1 which contains the summary statistics for the monthly dependent and explanatory variables (in percent) used in our time-series regressions. From the sample statistic of the explanatory variables we see that the average value of the market premium is quite high 0.64% per month and statistically significant. Among two other variables, size related factor premium (average SMB returns) is 0.16% with an insignificant t-statistics of 1.51, and BE/ME factor premium (average HML returns) is 0.51% per month with a significant t-statistics of 4.45. Looking at the average winner-minus-loser return estimates, we observe that both past-return based zero-investment strategy is profitable in our sample. The average momentum (reversal) WML return is 1.24% (0.59%) per month with a significant t-statistics of 5.06 (2.78). The summary statistics also suggests relatively low correlations between excess market, SMB, HML and two zero-investment portfolios. Therefore, our preliminary investigation indicates a statistically robust role at least for the market and the value-growth factor. Also, very low correlations across regressors in panel B suggest the absence of multicollinearity and autocorrelations which further influence their effectiveness as independent variables.

In Table 2 we report the summary statistic for all momentum and reversal decile portfolios. From the first panel we observe that for all momentum portfolios, the range of average excess returns varies from 0.13% to 1.27% per month. Except two smallest decile portfolios, the significant t-statistics justifies the robustness of the average short-term momentum returns. This result is consistent with earlier works of Grundy & Martin (2001) and Chordia & Shivakumar (2006).

Table 1
Mean, standard deviations, and correlation coefficients of the risk factors; July 1965 to June 2007

Panel A: Mean, standard deviations and t-statistics					
	Mkt	SMB	HML	WML^{SR}	WML^{LR}
Mean (%)	0.64	0.16	0.51	1.24	0.59
Std. dev (%)	5.43	3.36	3.57	7.63	6.46
t-stat (mean=0)	3.69	1.51	4.45	5.06	2.78
Panel B: Correlation and cross-autocorrelation coefficients					
	Mkt	SMB	HML	WML^{SR}	WML^{LR}
Mkt	1.00				
SMB	0.33	1.00			
HML	0.23	0.09			
WML^{SR}	-0.36	-0.29	-0.34	1.00	
WML^{LR}	-0.20	-0.51	-0.55	0.36	1.00
	Mkt	SMB	HML	WML^{SR}	WML^{LR}
Lag = 1	0.10	0.14	0.16	0.05	-0.004
Lag = 6	-0.02	-0.01	0.01	0.04	0.06
Lag = 12	-0.004	0.02	0.03	0.06	0.02
Lag = 20	-0.04	-.005	-0.01	-0.02	-0.01

Notes: For short-term returns the portfolio formation months are $t-12$ to $t-2$, and for long-term returns the portfolio formation months are $t-60$ to $t-13$. Mkt is the excess market return; SMB and HML are value weighted returns on factor mimicking portfolios for size and book-to-market. WML^{SR} is the average portfolio return constructed by subtracting short-term losers from winners at each time period. $WML^(LR)$ is the average portfolio return constructed by subtracting long term losers from winners at each time period.

Table 2
Descriptive statistics for 10 decile portfolios formed on past returns; July 1965 to June 2007

	Low	2	3	4	5	6	7	8	9	High
Panel A: Mean, standard deviations and t-statistics of excess returns for short-term momentum returns										
Full period										
Mean	0.13	0.30	0.42	0.56	0.56	0.63	0.72	0.86	0.95	1.27
Std Dev	9.59	8.12	7.00	6.46	6.00	5.86	5.62	5.42	5.70	6.53
t-stat (mean=0)	0.10	1.62	1.88	2.72	2.92	3.36	4.00	4.93	5.21	6.06
$\% > 0$	48.86	53.10	53.93	55.06	57.13	56.92	59.19	59.92	61.26	61.26
Panel B: Mean, standard deviations and t-statistics of excess returns for long-term reversal returns										
Full period										
Mean	1.20	1.01	0.98	0.79	0.84	0.73	0.76	0.75	0.61	0.61
Std Dev	8.84	7.86	6.93	6.13	6.20	5.71	5.91	5.71	5.78	6.33
t-stat (mean=0)	4.12	3.88	4.30	3.91	4.12	3.90	3.92	3.98	3.24	2.90
$\% > 0$	55.77	58.86	57.73	58.61	60.02	59.48	54.20	56.17	58.50	56.32

Notes: For short-term returns the portfolio formation months are $t-12$ to $t-2$, and for long-term returns the portfolio formation months are t-60 to $t-13$.

Interestingly, the portfolio sorted on 12-months past returns shows much stronger variation in average returns than the portfolios sorted on 60-months past returns. For both type of past return based portfolios, almost all the time, slightly over 50% of the months realize a positive payoff.

In Table 3 we report the regression estimate of the simple market and 3F model discussed in subsection 3.1. The significance of the coefficients (indicated with (*), (**), and (***)), are based on t-statistics that are adjusted for heteroskedasticity and autocorrelation of up to 12 lags. From the estimated slope and intercept coefficient it is apparent that the market model does not explain the relative return variability of the momentum portfolios at all. The CAPM alpha captures most of the variation in all 10 decile portfolios but the CAPM betas do not show much dispersion in the risk loadings. For the momentum returns, the WML alpha is 1.57% per month for the market model, and 1.84% per month for the 3F model. The result also indicates that controlling for SMB and HML do not solve the short-term momentum puzzle. For long-term return, however, the reverse is true. The trend in slopes and intercepts establishes the importance of size and value-growth risk factor in explaining the variability of reversal returns. Interestingly, the WML alpha for the reversal portfolio goes down from a significant value of -0.425 for the market model to an insignificant value of 0.055 for the 3F model. In other words, the 3F model estimation result clearly illustrates that controlling for SMB and HML do not exacerbates the reversal returns; in fact it helps to solve it.

Table 3
Simple CAPM regression results of monthly excess stock returns (in percent) of 10 portfolios formed on the decile breakpoints for various past returns ; July 1965 to June 2007

	Deciles										
	Low	2	3	4	5	6	7	8	9	High	WML
Panel A: Market model estimation based on short-term momentum returns											
b_0	-0.85***	-0.42**	-0.33*	-0.14*	-0.10	-0.02	0.09	0.25**	0.33**	0.61**	1.57***
b_1	1.42***	1.31***	1.06***	1.09***	1.03***	1.02***	0.97***	0.93***	0.96***	1.02***	-0.50**
R^2	0.74	0.78	0.82	0.84	0.85	0.83	0.82	0.81	0.84	0.71	0.13
Panel B: Market model estimation based on long-term reversal returns											
b_0	0.29**	0.14*	0.20**	0.08	0.12	0.06	0.06	0.07	-0.06	-0.12*	-0.42**
b_1	1.30***	1.23***	1.11***	1.01***	1.07***	0.99***	1.03***	1.01***	1.02***	1.10***	-0.24**
R^2	0.66	0.60	0.57	0.63	0.61	0.64	0.57	0.60	0.59	0.60	0.14
Panel C: Estimation results of three factor model for short-term momentum returns											
b_0	-1.11***	-0.58***	-0.45***	-0.24**	-0.19*	-0.09	0.07	0.26**	0.35**	0.72***	1.84***
b_1	1.31***	1.21***	1.12*	1.06***	1.00***	1.04***	0.98***	0.95***	0.97***	1.02***	-0.34***
b_2	0.57**	0.22**	0.06	0.03	-0.01	0.01	-0.05	-0.05	-0.01	0.15**	-0.42***
b_3	0.34**	0.34**	0.27**	0.23**	0.21*	0.15*	0.05	-0.01	-0.05	-0.25**	-0.59***
$\hat{R}^2$	0.77	0.73	0.70	0.81	0.86	0.82	0.74	0.81	0.70	0.69	0.20
Panel D: Estimation results of three factor model for long-term reversal returns											
b_0	-0.07	-0.13	-0.01	-0.05	0.00	-0.10	0.02	0.05	-0.02	-0.02	0.05
b_1	1.06***	1.04***	1.03***	0.97***	1.02***	0.97***	1.03***	1.02***	1.05***	1.01***	0.10
b_2	0.95***	0.39**	0.22*	0.10	-.025*	-0.08	-0.10	-0.12*	-0.12*	0.01	-0.95***
b_3	0.62***	0.60***	0.50***	0.33**	0.34**	0.25**	0.16**	0.09	-0.05	-0.32**	-0.94***
$\hat{R}^2$	0.71	0.66	0.68	0.69	0.67	0.70	0.65	0.64	0.63	0.68	0.51

Notes: For all 10 portfolios, the dependent variable is equal-weighted simple returns in excess of the one-month bill rate calculated for each month. For short-term returns the portfolio formation months are $t-12$ to $t-2$, and for long-term returns the portfolio formation months are $t-60$ to $t-13$. For Panel A-B we use the model: $r_t = b_0 + b_1 Mkt_t + e_t, e_t | \prod_{t-1} (0, \sigma^2), t = 1, \ldots T$. For panel C-D we use the model: $r_t = b_0 + b_1 Mkt_t + b_2 HML_t + b_3 SMB_t + e_t, e_t | \prod_(t-1) (0, \sigma^2), t = 1, \ldots T$. Mkt_t is the excess market return; SMB_t and HML_t are value weighted returns on factor mimicking portfolios for size and book-to-market. The t-statistics are adjusted for heteoskedasticity and autocorrelation of up to 12 lags. The regression R^2 are adjusted for degrees of freedom. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

Table 4 reports the estimated 3F model (2) in the presence of conditional variance specification (4) for two sets of portfolio returns. For the momentum portfolios the intercepts increases monotonically as we move from loser portfolios to winner portfolios. Compare to Table 3, accounting for conditional heteroskedasticity (in Table 4) reduces the magnitude of the absolute value of estimated coefficients but the general trend is still pervasive. The benefit of time-varying variance is reflected in adjusted R^2 and it clearly shows a marked improvement for all decile portfolios. What is most interesting is the payoff to the strategy of buying winners and selling losers. For the simple 3F model with time-varying conditional variance, the risk adjusted payoff goes down to 1.36% per month (compare to 1.84% in Panel C of Table 3) but remains statistically significant. Therefore, the result suggests that, even after controlling for Fama-French common risk factors, and accounting for heteroskedasticity, the associated risk of loser portfolio is still higher than the winner portfolios, although the latter earns a higher return. In terms of other slopes coefficients, the HML loadings spread between winners and losers increases marginally as we include time-varying conditional variance in the 3-factor model. The trend is exactly opposite for SMB loadings spread between winners and losers portfolios. The result is unaffected when we split the bottom and top deciles in half and construct four extreme portfolios as well. For long-term reversal returns, the general trend of Table 3 remains unchanged in Table 4. The only difference is that now the HML loading reveals an asymmetric pattern. The adjusted R^2 changes slightly.

Next in Table 5 we report the estimation results for the homoskedastic version of Carhart (1997) model (4). For the momentum portfolios, neither HML nor SMB seems to explain the general pattern in average returns, a fact we also observed in panel C of Table 3 and Panel A of Table 4. The zero-investment momentum portfolio, however, captures the spread and overall pattern in all 10 decile portfolios. The coefficient of WML^{SR} increases monotonically from -0.58 for the loser portfolio to 0.41 for the winner portfolio. More importantly, all of the estimated intercepts becomes economically and statistically insignificant. Therefore, the 4F model does not fail to capture the impact of short-term past return on future returns. This pronounced pattern and significant role of the additional factor based on long-short momentum portfolio re-establishes the earlier work of Carhart (1997) and Chordia & Shivakumar (2002) in our setting.

Table 4
Three factor regression results of monthly excess stock returns (in percent) of 10 portfolios formed on the decile breakpoints for various past-returns with conditional heteroskedasticity; July 1965 to June 2007

	Deciles										
	Low	2	3	4	5	6	7	8	9	High	WML
Panel A: Estimation results of three factor model with GARCH(1,1) error process for short-term momentum returns											
b_0	-0.83***	-0.41**	-0.21*	-0.11	-0.08	-0.03	0.06	0.19*	0.25**	0.50***	1.36***
b_1	1.15***	1.03***	0.95***	0.97***	0.94***	0.99***	1.00***	0.98***	1.02***	1.10***	-0.03
b_2	0.60***	0.17*	0.04	-0.01	-0.00	-0.01	-0.09	-0.08	-0.03	0.13	-0.49***
b_3	0.19**	0.10	0.08	0.10	0.12	0.10	0.04	-0.01	-0.05	-0.18*	-0.41**
β_1	0.19*	0.25**	0.30**	0.21*	0.15*	0.16*	0.13*	0.12*	0.08*	0.24**	0.21*
β_2	0.77***	0.72***	0.66***	0.76***	0.83*	0.77***	0.80***	0.84***	0.89***	0.67***	0.75***
$\hat{R}^2$	0.80	0.81	0.84	0.86	0.88	0.91	0.89	0.88	0.85	0.74	0.24
Panel B: Estimation results of three factor model with GARCH(1,1) error process for long-term reversal returns											
b_0	-0.15*	-0.05	.001	0.01	-0.01	-0.01	0.04	0.03	-0.01	-.002	0.09
b_1	1.05***	0.97***	0.95***	0.91***	0.98***	0.95***	1.00***	1.02***	1.04***	1.18***	0.12
b_2	0.86***	0.29*	0.14	0.06	-0.06	-0.10	-0.15*	-0.12	-0.09	0.06	-0.80*
b_3	0.56***	0.38*	0.33*	0.18*	0.17*	0.12	0.06	0.02	-0.11	-0.28*	-0.88*
β_1	0.04*	0.10*	0.12*	0.11*	0.13*	0.14**	0.15**	0.14**	0.12*	0.14**	0.08*
β_2	0.94***	0.87***	0.84***	0.86***	0.82***	0.80***	0.83***	0.80***	0.82***	0.80***	0.89***
$\hat{R}^2$	0.79	0.80	0.81	0.85	0.86	0.83	0.81	0.85	0.86	0.84	0.53

Notes: For all 10 portfolios, the dependent variable is equal-weighted simple returns in excess of the one-month bill rate calculated for each month. For short-term returns the portfolio formation months are $t-12$ to $t-2$, and for long-term returns the portfolio formation months are $t-60$ to $t-13$. For panel A-B we use the model: $r_t = b_0 + b_1 Mkt_t + b_2 HML_t + b_3 SMB_t + e_t, e_t | \prod_{t-1} (0, V_t), V_t = \beta_0 + \beta_1 e^2_{t-1} + \beta_2 V_{t-1}, t = 1, \ldots T$. Mkt_t is the excess market return; SMB_t and HML_t are value weighted returns on factor mimicking portfolios for size and book-to-market. Regression coefficient b_0, b_1, b_2, and b_3 represent mean part of the model specification. Regression coefficient β_1 and β_2 represent slope parameters of the variance specification. The t-statistics are adjusted for heteoskedasticity and autocorrelation of up to 12 lags. The regression R^2 are adjusted for degrees of freedom. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

Interestingly, the important role of factor-mimicking portfolio for momentum do not replicates when we utilize a similar factor based on 60-months prior returns. Once we estimate all reversal decile portfolios using WML^{LR} as an additional factor, the trend in the corresponding slope coefficient indicates puzzling result. We see from panel B of Table 5 that the lower decile portfolios are strongly negatively correlated with WML^{LR}, while the higher decile portfolios are strongly positively correlated with WML^{LR}. This suggests that firm's exposure to factor-mimicking long-short portfolio systematically varies across the momentum deciles but not for the reversal deciles.

Table 5
Four factor regression results of monthly excess stock returns (in percent) of 10 portfolios formed on the decile breakpoints for various past returns; July 1965 to June 2007

	Deciles									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Estimation results of four factor model for short-term momentum returns										
b_0	-0.04	0.12	0.05	0.10	0.04	-0.02	0.01	0.05	-0.01	-0.05
b_1	1.16***	1.10***	1.02***	0.99***	0.96***	0.99***	0.99***	0.99***	1.04***	1.12***
b_2	0.33**	0.07	-0.05	-0.05	-0.06	-0.01	-0.04	-0.01	0.08	0.10
b_3	-0.01	0.11	0.11	0.12	0.14*	0.03	0.07	0.05	0.06	0.02
b_4	-0.58**	-0.38**	-0.27**	-0.18**	-0.12	-0.03	0.02	0.11	0.19**	0.41***
$\hat{R}^2$	0.80	0.83	0.81	0.83	0.88	0.91	0.89	0.88	0.85	0.74
GRS test statistic:	1.18									
GRS p-value:	0.302									
Panel B: Estimation results of four factor model for long-term reversal returns										
b_0	-0.03	-0.11	0.003	-0.04	0.01	-0.01	0.02	0.05	-0.03	-0.03
b_1	1.11***	1.14***	1.06***	0.99***	1.03***	0.97***	1.03***	1.01***	1.03***	1.11***
b_2	0.30***	0.04	0.02	-0.05	-0.11	-0.12*	-0.08	-0.04	-0.03	-0.08
b_3	0.22**	0.25*	0.28*	0.17*	0.25**	0.20**	0.17*	0.17*	0.10	-0.02
b_4	-0.68***	-0.37***	-0.23**	-0.16*	-0.09	-0.04	0.01	0.08	0.15**	0.31***
$\hat{R}^2$	0.85	0.86	0.88	0.89	0.90	0.90	0.90	0.91	0.90	0.89
GRS test statistic:	1.04									
GRS p-value:	0.409									

Notes: For all 10 portfolios, the dependent variable is equal-weighted simple returns in excess of the one-month bill rate calculated for each month. For short-term returns the portfolio formation months are $t-12$ to $t-2$, and for long-term returns the portfolio formation months are $t-60$ to $t-13$. For panel A-B we use the model: $r_t = b_0+b_1Mkt_t+b_2HML_t+b_3SMB_t+b_4WML_t+e_t, e_t|\prod_(t-1)\,(0,\sigma_t^2), t=1,...T$. Mkt_t is the excess market return; SMB_t and HML_t are value weighted returns on factor mimicking portfolios for size and book-to-market. Regression coefficient b_0, b_1, b_2, b_3, and b_4 represent mean part of the model specification. The coefficient b_4 in panel A and B represents the slope coefficients corresponding to WML^{SR} and WML^{LR} respectively. WML^{SR} and WML^{LR} are the short-term and long-term based zero-investment portfolios respectively. The t-statistics are adjusted for heteoskedasticity and autocorrelation of up to 12 lags. The regression R2 are adjusted for degrees of freedom. The GRS test statistic and its associated p-values are calculated using Gibbons *et al.* (1989). Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

Each panel of Table 5 also contains the GRS test statistic (which has a F distribution) and its associated p-values which are calculated using the results of Gibbons *et al.* (1989). The null hypothesis for GRS test statistic is that the estimated intercepts are equal to zero across all portfolios (i.e., decile 1 through decile 10). From panel A results, the insignificant GRS test statistics value (with its associated p-value ¿0.05) fails to reject the null hypothesis that the 4F model is well specified for momentum portfolios. Panel B supports the same conclusion for reversal returns. Even though the adjusted R^2 shows some improvement, a natural question arises and it is about the role of endogenous information. Next we address that issue through a series of critical empirical test.

Table 6
Three factor regression results of monthly excess stock returns (in percent) of 10 portfolios formed on the decile breakpoints for various past returns with endogenous information and conditional heteroskedasticity; July 1965 to June 2007

	Deciles									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Estimation results of three factor model with GARCH(1,1) error process for short-term momentum returns										
b_0	-0.91***	-0.44**	-0.23*	-0.12	-0.08	-0.04	0.07	0.20*	0.26**	0.56***
b_1	1.14***	1.01***	0.94***	0.95***	0.94***	0.99***	1.01***	0.98***	1.02***	1.10***
b_2	0.56***	0.20**	0.05	0.00	-0.01	-0.01	-0.09	-0.08	-0.03	-0.10
b_3	0.15**	0.08	0.06	0.09	0.11	0.10	0.04	-0.01	-0.05	-0.19**
β_1	0.09*	0.19**	0.17**	0.17**	0.10	0.16*	0.14*	0.12	0.08	0.20**
β_2	0.79***	0.67***	0.70***	0.68***	0.80***	0.72***	0.74***	0.83***	0.89***	0.68***
β_3	-0.35***	-0.29***	-0.20**	-0.05	0.02	0.06	0.14**	0.18**	0.21**	0.27***
β_4	0.15**	0.15**	0.17**	0.23**	0.20**	0.14**	0.10	0.13**	0.10**	0.08*
$\hat{R}^2$	0.89	0.91	0.93	0.90	0.91	0.92	0.90	0.93	0.90	0.92
GRS test statistic:	11.16									
GRS p-value:	0.000									
Panel B: Estimation results of three factor model with GARCH(1,1) error process for long-term reversal returns										
b_0	-0.16*	-0.07	-0.03	-0.02	0.00	-0.01	0.04	0.03	-0.03	0.00
b_1	1.05***	0.98***	0.95***	0.91***	0.97***	0.96***	1.00***	1.02***	1.06***	1.18***
b_2	0.80*	0.28*	0.15*	0.08	-0.05	-0.10	-0.14*	-0.12	-0.09	-0.06
b_3	0.53*	0.39*	0.34*	0.22*	0.18*	0.12*	0.07	0.01	-0.11	-0.29*
β_1	0.06	0.05	0.08	0.04	0.11*	0.14*	0.11	0.13*	0.10	0.13*
β_2	0.88*	0.85*	0.86*	0.88*	0.80*	0.79*	0.83*	0.78*	0.81*	0.79*
β_3	0.05	0.07	-0.18**	-0.14**	0.09*	0.09	0.11*	0.05	0.04	-0.05
β_4	0.27***	0.23***	0.20**	0.19**	0.16**	0.15**	0.12**	0.11**	0.09*	0.06
$\hat{R}^2$	0.95	0.93	0.89	0.92	0.90	0.91	0.90	0.92	0.91	0.93
GRS test statistic:	1.88									
GRS p-value:	0.046									

Notes: For all 10 portfolios, the dependent variable is equal-weighted simple returns in excess of the one-month bill rate calculated for each month. For panel A and B we use the model: $r_t = b_0 + b_1 Mkt_t + b_2 HML_t + b_3 SMB_t + e_t, e_t | \prod_{t-1} (0, V_t), V_t = \beta_0 + \beta_1 e_{t-1}^2 + \beta_2 V_{t-1} + \beta_3 PI_{it-1} + \beta_4 NI_{it-1}, t = 1, \ldots T$. Mkt_t is the excess market return; SMB_t and HML_t are value weighted returns on factor mimicking portfolios for size and book-to-market. Regression coefficient b_0, b_1, b_2, and b_3 represent mean part of the model specification. Regression coefficient β_1, β_2, β_3, and β_4 represent slope parameters of the variance specification. For short-term returns the portfolio formation months are $t - 12$ to $t - 2$, and for long-term returns the portfolio formation months are $t - 60$ to $t - 13$. The t-statistics are adjusted for heteoskedasticity and autocorrelation of up to 12 lags. The regression R^2 are adjusted for degrees of freedom. The GRS test statistic and its associated p-values are calculated using Gibbons *et al.* (1989). Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

3.3 Pervasive role of endogenous information

In this subsection, first we report the findings of the statistical evaluation of our core idea whether endogenous information plays any role in discovering the variability of momentum and reversal returns. We start with Table 6, which contains the estimation of 3F regression model (2) stacked with endogenous information in the generalized variance specification (5). Panel A contains the estimation results for momentum portfolios. The average loading on SMB and HML decreases almost monotonically as we move from lower to higher decile portfolios. The most striking outcome is the coefficients of the positive information (i.e., PI_{it-1}) in the generalized variance specification. It starts with -0.35 for lowest decile portfolios and increases gradually to 0.27 for highest decile portfolios. Seven out of ten slope coefficients are statistically significant at the 5% level. Therefore, the elements of endogenous information associated with PI_{it-1}, successfully captures the patterns in average stock returns of momentum decile portfolios. The lagged value of negative information (i.e., NI_{it-1}), however, fails to capture the variability of average momentum portfolio returns. The slope coefficient of NI_{it-1} shows no clear cut pattern. Except two upper decile portfolios, namely 8th and 9th, the volatility persistent parameters do not cross 0.90 magnitudes. There is however one drawback of panel A results, and it is the high value of GRS test statistics and its associated low p-value. But as well see later, by incorporating the zero-investment factor in the mean model specification, we overcome that issue.

For the set of reversal portfolios, regression estimates from panel B suggests that the intercepts are consistently small. The lower deciles produce larger slopes on SMB and HML. What is surprising however is the statistically and economically meaningful role of negative endogenous information. The slope coefficient of NI_{it-1} starts with 0.27 for lowest decile portfolios and decreases gradually to 0.06 for highest decile portfolios. More importantly, nine out of ten slope coefficients turn out to be statistically significant at the 5% level. The GRS test statistic never rejects the hypothesis that the 3F model describes average reversal returns. Also, in terms of overall model fit, the value of average R^2 shows marginal improvement.

Our final scoreboard on common variation in average stock returns, reported in Table 7, extends the previous results by using a Carhart (1997) type 4F mean specification (3) in the presence of (5). We observe that the results of Table 7 are very much similar to Table 6 except some minor differences. For the momentum returns, the trend in the slope of WML^{SR} in panel A is still very pronounced. On top of that, the incorporation of a zero-investment portfolio even strengthens the role of the positive endogenous information. Given the strong slopes of SMB and HML, it is not surprising that adding a zero-investment portfolio in the mean specification, and endogenous information in the generalized variance specification, results in larger improvement in the coefficient of determination. Interestingly, WML^{SR} also reduce the market beta magnitudes toward 1.0. For lower decile portfolios, the effect on market beta is stronger than the higher decile portfolios. This result altogether should not be surprising as there is positive correlation between the market and common risk factors, and negative correlation between market and zero-investment portfolio. Overall, the insignificant value of GRS test statistic and high average value of adjusted R^2 forces us to conjecture that, among all the model we have considered so far, specifications (3) and (5) captures the best possible description of momentum returns.

Table 7
Four factor regression results of monthly excess stock returns (in percent) of 10 portfolios formed on the decile breakpoints for various past returns with endogenous information and conditional heteroskedasticity; July 1965 to June 2007

	Deciles									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Estimation results of four factor model with GARCH(1,1) error process for short-term momentum returns										
b_0	-0.12	0.06	0.06	0.05	0.05	-0.04	-0.03	-0.01	-0.08	-0.10
b_1	1.16***	1.03**	0.96**	0.96**	0.94**	0.99**	1.00**	1.01**	1.05**	1.09**
b_2	0.37**	0.13*	0.03	-0.01	-0.02	-0.01	-0.06	-0.002	0.10	0.16*
b_3	0.01	0.05	0.04	0.07	0.09	0.10	0.07	0.08	0.06	0.09
b_4	-0.52**	-0.31**	-0.22**	-0.14*	-0.09	0.00	0.06	0.15*	0.21**	0.45**
β_1	0.06	0.10*	0.13**	0.11	0.08	0.16**	0.15**	0.12**	0.14**	0.17**
β_2	0.91***	0.86***	0.75***	0.76***	0.83***	0.70***	0.73***	0.82***	0.80***	0.79***
β_3	-0.36**	-0.31**	-0.23**	-0.13**	0.01	0.04	0.09*	0.15**	0.23**	0.29**
β_4	0.08*	0.13**	0.14**	0.13**	0.13**	0.10**	0.10**	0.09**	0.04*	0.08*
$\hat{R}^2$	0.93	0.92	0.91	0.91	0.94	0.92	0.91	0.90	0.91	0.93
GRS test statistic: 1.65 (GRS p-value: 0.091)										
Panel B: Estimation results of four factor model with GARCH(1,1) error process for long-term reversal returns										
b_0	-0.09	-0.08	0.00	0.001	0.003	-0.01	0.04	0.02	-0.05	-0.07
b_1	1.15***	1.03***	1.00***	0.93***	0.97***	0.96***	0.99***	1.01***	1.05***	1.09***
b_2	0.30**	0.25**	0.11*	0.004	-0.07	-0.10	-0.12*	-0.05	-0.05	-0.10
b_3	0.40**	0.22**	0.16*	0.12*	0.14*	0.10	0.09	-0.10*	-0.14*	-0.13
b_4	-0.67**	-0.32**	-0.22**	-0.11	-0.04	0.001	0.04	0.08	0.15*	0.32**
β_1	0.06	0.04	0.11	0.05	0.11	0.14*	0.13*	0.14*	0.11*	0.15*
β_2	0.89***	0.90***	0.83***	0.88***	0.81***	0.79***	0.83***	0.79***	0.80***	0.82***
β_3	0.05	-0.24**	-0.35***	-0.05	0.02	0.02	0.06	0.01	0.003	0.04
β_4	0.17**	0.14**	0.11*	0.15**	0.13**	0.08*	0.10**	0.05	0.07	0.01
$\hat{R}^2$	0.94	0.89	0.92	0.90	0.91	0.93	0.90	0.91	0.92	0.91
GRS test statistic: 0.98 (GRS p-value: 0.460)										

Notes: For all 10 portfolios, the dependent variable is equal-weighted simple returns in excess of the one-month bill rate calculated for each month. For panel A and B we use the model: $r_t = b_0 + b_1 Mkt_t + b_2 HML_t + b_3 SMB_t + b_4 WML_t + e_t, e_t | \prod_(t-1)\ (0, V_t), V_t = \beta_0 + \beta_1 e_{t-1}^2 + \beta_2 V_{t-1} + \beta_3 PI_{it-1} + \beta_4 NI_{it-1}, t = 1, \ldots T$. Mkt_t is the excess market return; SMB_t and HML_t are value weighted returns on factor mimicking portfolios for size and book-to-market. Regression coefficient b_0, b_1, b_2, b_3, and b_4 represent mean part of the model specification. Regression coefficient β_1, β_2, β_3, and β_4 represent slope parameters of the variance specification. The coefficient b_4 in panel A and B represents the slope coefficients corresponding to WML^{SR} and WML^{LR} respectively. WML^{SR} and WML^{LR} are the short-term and long-term based zero-investment portfolios respectively. For short-term returns the portfolio formation months are $t-12$ to $t-2$, and for long-term returns the portfolio formation months are $t-60$ to $t-13$. The t-statistics are adjusted for heteoskedasticity and autocorrelation of up to 12 lags. The regression R^2 are adjusted for degrees of freedom. The GRS test statistic and its associated p-values are calculated using Gibbons *et al.* (1989). Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

Table 8
Robustness checks for four factor regressions of monthly excess stock returns (in percent) of 10 portfolios formed on the decile breakpoints for SR and LR past returns; July 1965 to June 2007

	Deciles									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Sub period regression estimates										
July 1927- June 1965										
PSR	-0.32***	-0.33***	-0.29***	-0.39***	0.08*	0.05*	0.12**	0.19**	0.18**	0.21**
NSR	0.10**	0.13**	0.09*	0.17**	0.12**	0.10**	0.14**	0.09*	0.07*	0.12**
PLR	0.04	-0.13*	-0.25**	-0.01	0.04*	0.08*	0.10**	0.02	0.001	0.07
NLR	0.19**	0.14**	0.15**	0.15**	0.18**	0.06*	0.10**	0.03*	0.10**	0.08**
July 1965- June 1989										
PSR	-0.29***	-0.31***	-0.32***	-0.37***	0.08*	0.07*	0.14**	0.19**	0.20**	0.23**
NSR	0.06*	0.10**	0.14**	0.13**	0.13**	0.15**	0.17**	0.09*	0.03	0.08*
PLR	0.08*	-0.15**	-0.32**	-0.08*	0.01	0.06*	0.05*	0.02	0.00	0.02
NLR	0.21**	0.19**	0.13**	0.07*	0.17**	0.19**	0.11**	0.09*	0.06*	0.07*
July 1989- June 2007*										
PSR	-0.33***	-0.28***	-0.22**	-0.35***	0.06*	0.03	0.10**	0.15**	0.19**	0.20**
NSR	0.03	0.09**	0.14*	0.12**	0.17**	0.10**	0.17**	0.10*	0.02	0.10*
PLR	-0.05*	-0.14**	-0.22*	-0.10**	0.08*	0.14*	0.03	0.01	0.04*	0.07*
NLR	0.24**	0.20**	0.17**	0.18**	0.10*	0.08*	0.14**	0.05*	0.10**	0.13**
Panel B: Rolling window estimates										
PSR	-0.30***	-0.27***	-0.22**	-0.16**	0.04*	0.10**	0.11**	0.17**	0.16**	0.18**
NSR	0.09*	0.12**	0.11**	0.15**	0.13**	0.11**	0.12**	0.08*	0.05*	0.10**
PLR	0.09*	-0.19*	-0.30**	-0.04*	0.02	0.04*	0.05*	0.03*	0.002	0.05*
NLR	0.25**	0.21**	0.19**	0.17*	0.12**	0.13**	0.12**	0.10**	0.09**	0.05*

Notes: For all 10 portfolios, the dependent variable is equal-weighted simple returns in excess of the one-month bill rate calculated for each month. In panel B, the four factor models are estimated each month using a rolling window of 60 prior monthly returns. For all results we use the model: $r_t = b_0 + b_1 Mkt_t + b_2 HML_t + b_3 SMB_t + b_4 WML_t + e_t, e_t | \prod_{t-1} (0, V_t), V_t = \beta_0 + \beta_1 e^2_{t-1} + \beta_2 V_{t-1} + \beta_3 PI_{it-1} + \beta_4 NI_{it-1}, t = 1, \ldots T$. Mkt_t is the excess market return; SMB_t and HML_t are value weighted returns on factor mimicking portfolios for size and book-to-market. Here PSR and PLR represent the β_3 coefficients corresponding to short-term and long-term returns respectively. Also, NSR and NLR represent the β_4 coefficients corresponding to short-term and long-term returns respectively. For short-term returns the portfolio formation months are $t - 12$ to $t - 2$, and for long-term returns the portfolio formation months are $t - 60$ to $t - 13$. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% level respectively.

For the reversal returns, the slope parameters and the associated t-statistics remain statistically robust, but do not show much improvement compare to our earlier estimation results of Table 6. From panel B of Table 7 we observe that both SMB and HML losses their explanatory power, and endogenous information resembles smaller economically meaningful role. For example, the average value of the NI_{it-1} slopes in panel B is 0.16 in Table 6, and 0.10 in Table 7. We suspect that the incorporation of the long-short portfolio has something to do with it since it has very high negative correlation with the market, SMB, and HML. In general, for the sets of reversal portfolios, panel B of Table 6 (i.e., specifications (2) and (5)) seems to produce the best possible outcome.

3.4 Interpretation of asymmetric endogenous information

It is important to note that our empirical results concerning the role of endogenous information are motivated by the observed patterns in returns, and it is therefore imperative that we interpret them carefully. What our result really means is that a prediction of high or low volatility of momentum (or reversal) return is simply a prediction of a big swing in momentum (or reversal) returns. What it does not imply however is perfect predictability of the magnitude of the swing. There is no doubt that the positive endogenous information does explain short-term persistence of momentum returns, and the negative endogenous information does much to explain long-term persistence of reversal returns.

Unlike the existing literature, which focuses on the first moment of momentum or reversal returns, we evaluate the second moment and it's relation to well-known predictors of volatility measure. As mentioned by Moskowitz (2003), the second moment of returns plays a vital role in asset-pricing theory. It is also widely known that investment strategies that account for the changing variance structure of returns are more efficient than portfolios that ignore such second moment dynamics (Graham & Harvey, 1996, Fleming *et al.*, 2001). Our paper therefore reconciles the existing work that shed light on the second moment of the return distribution as a possible explanation for some of the well-known anomalies.

We can also interpret the endogenous information as the priced risk factors since they help to forecast stock market returns volatility, which is along the argument pioneered by Merton (1973). As mentioned by Cochrane (2005, p.438) "asset pricing theory recognized at least since Merton... the theoretical possibility, indeed probability, that we should need factors, state variables, or sources of priced risk beyond movements in the market portfolio in order to explain why some average returns are higher than others". Even though ICAPM should not be used as a "fishing license", our endogenous information reflect a type of systematic risk, which emanates from a multifactor set up, and omitted from regular CAPM or 3F model. Without this additional covariate, the optimal portfolios need not be multifactor efficient.

4. Forecasting Excess Stock Returns

4.1 Sub-period regression and rolling window estimates

Overall, the regression slopes estimates and $\bar{R}^2$ values in Tables 6 and 7 re-establish that the market, SMB, and HML do proxy for risk factors. But the long-short portfolio and the elements of endogenous information capture an independent common variation in short-term momentum and long-term reversal returns. More importantly, the risk associated with this endogenous information is separate from the market or value-growth risk, and is compensated differently in expected returns.

Obviously, one can interpret the above mentioned role of endogenous information as data mining. In addition, even though the shared variation in average stock returns seems to be appealing, there can be many practical concerns about their analytical role in the model. Moreover, the exposure of momentum and reversal portfolios to the endogenous information may not be stable across sub periods and our model may not reflect the actual temporal variation in risk loadings. In order to avoid these problems and to check the robustness of our results we consider alternative statistical experiments – we replicate our analysis for various sub periods and rolling windows. We call them sub period regression estimates and rolling window estimates. The outcome of these experiments is reported in Table 8.

Panel A of Table 8 reports the relevant output for the coefficient on PI_{it-1} in equation (3) and (5) for momentum, and NI_{it-1} in equation (2) and (5) for reversal returns respectively.[13] The coefficient of PI_{it-1} seem to be stable across various sub periods. It also depicts monotonically increasing trend from the loser portfolio to the winner portfolio; an empirical artifact we already saw in Table 6 and 7. The sub period July 1927 to June 1965 produces the highest average value for PI_{it-1} slopes. The highest number of statistically significant PI_{it-1} slopes is for the sub period July 1989 to June 2007. The corresponding figure for NI_{it-1} is for the sub period July 1965 to June 1989. The average value of the NI_{it-1} slopes is 0.13 for the sub period July 1965 to June 1989, and 0.12 for July 1989 to June 2007. Overall, even for various sub periods, positive endogenous information does not fail to capture the variability in the returns of momentum portfolios. The same is true for negative endogenous information for the portfolios of reversal returns.

Similar observation can be noted as we interpret the rolling window estimates from panel B of Table 8. We obtain the results by estimating our multifactor models for each month during July 1965 to June 2007 period using a rolling window of 60 prior monthly returns. The regression slope estimates in the five year rolling window procedure suggests that our multifactor model correctly captures the temporal variation in the loadings of both positive and negative endogenous information. For momentum deciles, the average value of PI_{it-1} slopes rolling window estimates is -0.02, and for reversal deciles, the average value of NI_{it-1} slopes rolling window estimates is 0.14. Overall, it indicates that even though true loadings are not constant, the estimate of period-by-period loading is close to what we observed before. Therefore, these robustness check results strongly support our earlier finding that the temporal variation in momentum (reversal) return is strongly captured by positive (negative) endogenous information.

4.2 In-Sample forecasting regressions

At this point, we are convinced about the pervasive role of endogenous information but we haven't talked about over parameterization issue. One of the easiest way to investigate that issue is to use in-sample goodness-of-fit statistics and out-of-sample volatility forecast corresponding to various alternative models described in Table 4, 6, and 7. In order to compare the in-sample and out-of-sample performance of various model specifications, following Marcucci (2005), we utilize four common statistical loss functions. They are two versions of mean squared error (MSE) and mean absolute deviation (MAD), and are given by the following:

[13] To conserve space, we only report the slope coefficients of PI_{it-1} and NI_{it-1} in Table 8. The full regression results are available from the authors upon request.

$$MSE1 = \frac{1}{n}\sum_{t=1}^{n}(\hat{\sigma}_{t+1}^{1/2} - \hat{V}_{t+1|t}^{1/2})^2,$$
$$MSE2 = \frac{1}{n}\sum_{t=1}^{n}(\hat{\sigma}_{t+1} - \hat{V}_{t+1|t})^2$$

$$MAD1 = \frac{1}{n}\sum_{t=1}^{n}|\hat{\sigma}_(t+1)^(1/2) - \hat{V}_{t+1|t}^{1/2}|, MAD2 = \frac{1}{n}\sum_{t=1}^{n}|\hat{\sigma}_(t+1) - \hat{V}_{t+1|t}|$$

where $\hat{sigma_(}t+1)$ is the true volatility and $\hat{V}_(t+1|t)$ is the 1-step ahead volatility forecast made at time t. For the in-sample results, the estimation period is from July 1965 through June 2007. For the evaluations of our out-of-sample performance, we use the last 5 years observations from July 2002 through June 2007.

Table 9 reports the results. Here k refers to the number of the parameters being estimated in each model, AIC is the Akaike information criterion, SIC is the Schwartz information criterion, $LogL$ is the log likelihood value, and PER is the persistent of the shocks to the conditional variance.

Table 9
In-sample and out-of-sample performance of median momentum and reversal portfolio models

		Panel A: In-sample performance								
Models		Goodness-of-fit statistics					In-sample			
		k	logL	AIC	SIC	PER	MSE1	MSE2	MAD1	MAD2
1	Momentum	7	-2524.6	-2529.2	-2537.3	0.98	4.53	1.82	1.04	1.02
1	Reversal	7	-2201.7	-2209.2	-2212.1	0.95	4.50	1.78	1.01	0.99
2	Momentum	9	-2487.2	-2492.7	-2499.2	0.90	4.51	1.78	1.01	1.00
2	Reversal	9	-2152.4	-2190.5	-2192.7	0.91	4.48	1.71	0.94	0.85
3	Momentum	10	-2450.1	-2451.8	-2452.5	0.91	4.50	1.77	0.99	1.00
3	Reversal	10	-2190.1	-2263.4	-2201.1	0.92	4.46	1.74	0.97	0.89
		Panel B: Out-of-sample performance								
Models		Out-of-sample				Sign test				
		MSE1	MSE2	MAD1	MAD2	SR				
1	Momentum	22.33	7.78	1.99	2.50	0.55				
1	Reversal	20.66	6.98	1.89	2.24	0.68				
2	Momentum	21.50	7.53	1.96	2.42	0.62				
2	Reversal	19.20	5.89	1.57	2.12	0.79				
3	Momentum	21.09	7.42	1.95	2.41	0.67				
3	Reversal	19.18	6.07	1.68	2.19	0.75				

Notes: Here k refers to the number of parameters being estimated in each model. AIC is the Akaike information criterion. SIC is the Schwartz information criterion. PER is the persistence of the shocks to the conditional variance. MSE1, MSE2, MAD1, and MAD2 are the loss functions as defined in the text. Model 1-3 for median momentum and reversal portfolio are detailed in subsection 4.2.

Model 1 of median momentum and reversal portfolio is based on Table 4 (i.e., panel A and B respectively). Model 2 corresponds to Table 6 (i.e., panel A for median momentum and panel B for median reversal returns). We also express model 3 using the specification of Table 7 where panel A is for median momentum and panel B is for median reversal returns.

We observe that in terms of log-likelihood corresponding to various median momentum portfolios, the largest value corresponds to Model 3 (i.e., panel A specification of Table 7). For the reversal portfolio, the largest log-likelihood value belongs to model 2 (i.e., panel B of Table 6). In terms of model selection criterion, both AIC and SIC indicates that the best median momentum model is panel A of Table 7, and best median reversal model is panel B of Table 6.

However, the persistence parameter of the best momentum model is not lowest, even though the estimate is highly reduced compare to model 1 (i.e., panel A of Table 4). Interestingly, for the best median reversal model we don't see such problem. In terms of MSE and MAD based performance, the best median momentum and reversal model always performs at least as good as the other two. Only exception is the MSE1 for the median reversal portfolio, as model 2 has slightly higher value compare to model 3.

4.3 Out-of-Sample forecast comparisons

In terms of the out-of-sample results of panel B, performance of model 3 of median momentum and model 2 of reversal portfolio is consistent with our earlier conclusion. The pair of MSE and MAD of model 2 for median momentum portfolio is always lowest. For the median reversal portfolio, only the MSE1 for model 3 is slightly better. In order to measure the accuracy of sign of volatility forecasts for various momentum and reversal models, we also use a sign test, known as the so called success ratio (SR). The SR test is simply based on the fraction of the volatility forecasts that has the same sign as the volatility realizations and is given by

$$SR = \frac{1}{n}\sum_{(} j=0)^{(}n-1)1_{(}[\hat{\sigma}_{(}t+j)\hat{V}_{(}t+j|t+j-1)>0])$$

where $\hat{\sigma}_{(}t+j)$ is the proxy for the actual volatility after subtracting its non-zero mean, $\hat{V}_{(}t+j|t+j-1)$ is the volatility forecasts after substracting the corresponding mean, and $1_{[g>0]}$ is an indicator function, i.e., $1_{[g>0]} = 1$ if g is positive and zero otherwise. From the results of the last column of panel B we see that the model 3 for median momentum portfolio return does the best job in correctly predicting the sign of future volatility. Similarly, model 2 for median reversal portfolio has the best ability to predict correct sign of the volatility forecasts. In summary, not to our surprise, what we observe closely resembles our conclusions from section 3.

5. Conclusions

In the empirical asset-pricing literature, short-term price momentum and long-term price reversal are two of the most-studied anomalies. Momentum, in particular, has gained tremendous attention, as it is not explained by the Fama & French (1993) three-factor model, and provides evidence against market efficiency. There exist numerous sets of alternative explanations for such apparent anomalies and in this paper we attempt to provide a complementary risk-based approach. The goal is to establish an economic link between the anomalies and variance risk. We show that it is possible to construct uneven endogenous information using the lagged values of portfolio returns, and it can help us to explain a sizeable part of the anomalous pattern of momentum and reversal returns. We illustrate that even in the presence of a zero-investment portfolio, spreads in average momentum and reversal returns correspond to spreads in the slopes of the endogenous information. The results also indicate that one can easily use the asymmetric endogenous information as a performance attribution factor. Taken together, our results for both momentum and reversal portfolios suggest that the returns are influenced by a random endogenous information flow that is hidden in historical behavior. If we fail to incorporate such asymmetric information, any attempt to explore average stock return predictability will be subject to an unquantified specification bias.

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