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Momentum and Behavioral Finance

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Momentum and Behavioral Finance

1. Introduction

There is substantial domestic and international evidence of momentum in individual stock returns of 1 week to 12 months.[1] Whether momentum is due to risk or behavioral biases is a critically important question to both theoretical asset pricing and practical investment decision making.

Many studies rely on structural asset pricing models such as the CAPM and the three-factor model of Fama and French (1996) to examine the sources of momentum. They find that risk adjustment in general does not explain momentum (see Jegadeesh and Titman, 1993; Fama and French, 1996; and Grundy and Martin, 2001 among others).[2] However, using structural asset pricing models results in a joint test of the validity of the structural model for what constitutes relevant risk factors and the validity of the hypothesis that momentum is due to risk. If any such structural model has specification error or does not account for all risk factors, test results based on the model will be unreliable.

An alternative approach is implied by Lo and MacKinlay (1990) (LM), which suggests that there are three sources of momentum profits: (positive) serial correlation, (negative) cross-serial correlation, and dispersion in unconditional mean returns. Conrad and Kaul (1998) indicate that if expected returns are assumed to be constant over time, the three momentum components based on the LM decomposition will be closed tight to alternative explanations of momentum. Specifically, if expected returns are time invariant, unconditional mean returns become an unbiased estimator of true expected returns of stocks. Consequently, dispersion in unconditional mean returns will explain momentum if momentum is due to risk. On the other hand, momentum will be explained by cross-serial correlation or serial correlation if momentum is due to behavioral biases suggested by LM, Barberis, Shleifer, and Vishny (1998) (BSV), Daniel, Hirshleifer, and Subrahmanyam (1998) (DHS), and Hong and Stein (1999) (HS). Conrad and Kaul (1998) utilize the LM methodology and find that all of the observed momentum profits can be explained by dispersion in unconditional mean returns, which suggests a risk-based explanation for momentum.

[1] See Jegadeesh and Titman (1993), Rouwenhorst (1998), Chan, Hameed and Tong (2000), Moskowitz and Grinblatt (1999), Hong, Lim, and Stein (2000), Lee and Swaminathan (2000), Jegadeesh and Titman (2001), Balvers and Wu (2006), and Hvidkjaer (2006). One anomaly within this literature is the reversal in individual stock returns of one week to one month documented by Lehmann (1990) and Jegadeesh (1990). However, Gutierrez and Kelley (2008) recently find that the brief reversal is followed by a long-lasting continuation in returns, and that momentum in individual stock returns up to one year is indeed a pervasive phenomenon.

[2] Contrary to Chordia and Shivakumar (2002) who find that momentum can be explained by a set of lagged macroeconomic variables, Griffin, Ji, and Martin (2003) find that momentum has little relation to those macro variables.

However, Jegadeesh and Titman (2002) show that the LM methodology may be biased. Specifically, the LM methodology requires an estimate of the cross-sectional variance of true expected returns. As Jegadeesh and Titman (2002) show, although sample mean returns are unbiased estimates of true expected returns (assuming constant expected returns), the cross-sectional variance of sample mean returns in LM is not an unbiased estimator of the cross-sectional variance of true expected returns. Jegadeesh and Titman (2002) therefore do not use the LM methodology, but instead simply use sample mean returns to adjust momentum profits. They find that dispersion in unconditional mean returns does not explain momentum at all, which suggests a behavioral explanation for momentum.

One weakness in Jegadeesh and Titman (2002) is that they estimate unconditional mean returns based on the sample period that excludes the ranking and holding periods. Their approach effectively truncates the return distribution and can lead to bias. That is, unconditional mean returns based on the truncated sample in Jegadeesh and Titman (2002) may not be an unbiased estimator of true expected returns even if expected returns are constant. A recent study by Bulkley and Nawosah (2009) corrects this bias by using the entire sample period to estimate unconditional mean returns, and finds that momentum is still mainly explained by dispersion in unconditional mean returns.

It is, however, important to note that previous studies (i.e. Jegadeesh and Titman, 2002; Bulkley and Nawosah, 2009) focus only on two components of momentum profits: the component due to dispersion in unconditional mean returns and the component due to time-series dependence. They do not further decompose the component due to time-series dependence into the component due to serial correlation and that due to cross-serial correlation. Their approach therefore may underestimate the importance of time-serial dependence if the serial correlation component has opposite sign from the cross-serial correlation component.

Motivated by this observation, we revisit the issue of the sources of momentum profits. We utilize a decomposition methodology proposed by Du and Watkins (2007) which enables an unbiased decomposition of momentum profits into three relevant components (i.e. dispersion in unconditional mean returns, serial correlation and cross-serial correlation).[3] Empirically, we focus on two commonly studied momentum strategies for robustness. One is the long-horizon momentum investigated by Jegadeesh and Titman (1993), while the other is the short-horizon momentum recently studied by Gutierrez and Kelley (2008). For both momentum strategies, we find that dispersion in unconditional mean returns is statistically and economically important to explain momentum profits in U.S. individual stock returns. This finding is consistent with Bulkley and Nawosah (2009) and suggests that momentum may be at least partly due to risk.

[3] Du and Watkins (2007) focus on momentum in portfolio returns, while the present paper looks at momentum in individual stock returns.

We also find that, for both momentum strategies, the serial correlation component has opposite sign from the cross-serial correlation component.[4] As a result, the time-series component as a whole explains very little momentum profits. Given that both components due to time-series dependence are significant, the conclusion in Bulkley and Nawosah (2009) may be open to question in that momentum may also be at least partially due to behavioral biases. Therefore, taken together, our findings suggest that momentum may have multiple sources. Risk or behavioral biases in isolation may not be sufficient to explain momentum.

The remainder of the paper is organized as follows: Section 2 describes the data and investigates the momentum in monthly returns. Section 3 examines sources of the momentum. Section 4 concludes the manuscript.

2. Momentum in Monthly Returns

2.1 Data

U.S. individual stocks are used for empirical investigation. The monthly stock returns are from CRSP. The Fama-French factor data are downloaded from Kenneth French's website.[5] To be comparable with relevant studies (i.e. Gutierrez and Kelley, 2008), we focus on the sample period from 1983 to 2007.

2.2. Momentum Profits

Two popular decile-based momentum strategies are considered. One is the short-horizon momentum of Gutierrez and Kelley (2008), while the other is the long-horizon momentum of Jegadeesh and Titman (1993).

For the short-horizon momentum, at the beginning of each month *t*, stocks are ranked in ascending order on the basis of their returns during the past month (t-1). Based on these rankings, ten equally-weighted decile portfolios are formed. For each month *t*, the momentum portfolio goes long in the top decile (winners) and short in the bottom decile (losers) in an equally-weighted fashion. To minimize the microstructure effects, we skip one month between the ranking period and the holding period.[6] To match the commonly-investigated holding period, these positions are held for six months from t+2 to t+7. To evaluate the performance of the momentum portfolio over holding periods longer than one month, we follow Jegadeesh and Titman (1993) and Gutierrez and Kelley (2008), and employ the calendar-time

[4] This finding is consistent with the portfolio momentum results in Lewellen (2002).

[5] We thank Fama and French for making these data available.

[6] One month is usually skipped to minimize the microstructure effects. Jegadeesh and Titman (1993, 2001) and Fama and French (1996) among others have used this skipping filter to better gauge momentum profits. Recently, Griffin, Ji, and Martin (2002) and Cooper, Gutierrez, and Hameed (2004) question the ability of macroeconomic models to explain momentum with this filter.

method. The calendar-time method avoids overlapping returns and the accompanying strongly positive serial correlation in returns while allowing all possible holding periods to be considered. We also follow Gutierrez and Kelley (2008) to exclude stocks with a price below $5 at the end of ranking period (t-1) to mitigate microstructure effects associated with low-price stocks. The long-horizon momentum portfolio is constructed in the same fashion except that the momentum strategy is based on past six month returns (t-6 to t-1).

Table 1 reports the mean momentum profits and the associated t- ratios. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12 (or one year). Jegadeesh and Titman (1993) suggest that there may be seasonality in momentum profits. Table 1 therefore distinguishes between January and other calendar months. The section headed by "1 Month/6 Month" presents the profits for the winner, the loser and the winner-minus-loser (WML) portfolios with one-month ranking and six-month holding periods (i.e. the short-horizon momentum). Consistent with Gutierrez and Kelley (2008), there is significant short-horizon momentum in returns. The mean profit for all months is 0.32% per month with a t-statistic of 3.04. Outside January, the momentum profit is slighter higher, which is 0.38% per month with a t-statistic of 3.18.

Table 1. Momentum Profits

	1 Month/6 Month			6 Month/6 Month		
	All	**Jan**	**Non-Jan**	**All**	**Jan**	**Non-Jan**
Winner	0.0178 (6.07)	0.0454 (4.59)	0.0160 (5.21)	0.0185 (6.28)	0.0384 (3.82)	0.0167 (5.36)
Loser	0.0146 (5.27)	0.0508 (3.73)	0.0121 (3.92)	0.0133 (4.85)	0.0546 (3.21)	0.0096 (2.99)
W-L	0.0032 (3.04)	-0.0054 (-0.81)	0.0038 (3.18)	0.0051 (2.75)	-0.0162 (-1.15)	0.0071 (3.58)

Table 1 reports the mean momentum profits and the associated t- ratios. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12 (or one year). Table 1 also distinguishes between January and other calendar months. The section headed by "1 Month/6 Month" presents the profits for the winner, the loser and the winner-minus-loser portfolios with one-month ranking and six-month holding periods (i.e. the short-horizon momentum). The section headed by "6 Month/6 Month" presents the profits for the winner, the loser and the winner-minus-loser portfolios with six-month ranking and six-month holding periods (i.e. the long-horizon momentum).

The section headed by "6 Month/6 Month" presents the profits for the winner, the loser and the winner-minus-loser (WML) portfolios with six-month ranking and six-month holding periods (i.e. the long-horizon momentum). Consistent with Jegadeesh and Titman (1993), there is significant long-horizon momentum in returns. The mean profit for all months is 0.51% per month with a t-statistic of 2.75. Outside January, the momentum profit is higher, which is 0.71% per month with a t-statistic of 3.58.

Therefore, consistent with Jegadeesh and Titman (1993), momentum strategies in our sample are also usually not profitable in the month of January. However, since the differences between the profits based on all months and those based on non-January months are relatively small,[7] for brevity, our discussion will focus on all-month results in subsequent sections.

3. Sources of Momentum

3.1 Sources of Momentum Profits Based on Structural Models

Many studies rely on structural asset pricing models such as the CAPM and the three-factor model of Fama and French (1996) to examine the sources of momentum profits. To calculate CAPM risk-adjusted profits, the momentum profit is regressed on a constant and the excess market return,

$$WML_t = \alpha - \beta EM_t + \varepsilon_t \qquad (1a)$$

where WML_t is the momentum profit from the winner-minus-loser portfolio in month t, EM_t is the excess market return in month t, and ε_{it} is the disturbance. The risk-adjusted profits (WML_t^{adj}) are

$$WML_t^{adj} = WML_t - \hat{\beta} EM_t \qquad (1b)$$

where $\hat{\beta}$ is the estimated CAPM beta. One can also adjust the risk by the Fama-French three factor model in the same fashion.

Table 2 reports the risk-adjusted momentum profits and the associated t- ratios. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12 (or one year). Table 2 also distinguishes between January and other calendar months. The section headed by “1 Month/6 Month” presents the risk-adjusted profits for the winner, the loser and the winner-minus-loser (WML) portfolios with one-month ranking and six-month holding periods (i.e. the short-horizon momentum). Consistent with Gutierrez and Kelley (2008), risk adjustment based on the structural asset pricing models does not explain the short-horizon momentum. The CAPM risk-adjusted profit for all months is 0.36% per month with a t-statistic of 3.68, while the three-factor model risk-adjusted profit is 0.40% per month with a t-statistic of 2.84.

The section headed by “6 Month/6 Month” presents the profits for the winner, the loser and the winner-minus-loser (WML) portfolios with six-month ranking and six-month holding periods (i.e. the long-horizon momentum). Again, consistent with Jegadeesh and Titman (1993), Fama and French (1996), and Grundy and Martin (2001), risk adjustment based on the structural asset pricing models does not explain the long-horizon momentum. The CAPM risk-adjusted profit for all months is 0.53% per month with a t-statistic of 3.19, while the three-factor model risk-adjusted profit is 0.64% per month with a t-statistic of 2.83.

[7] This may be due to that we exclude low-price stocks.

Table 2. Sources of Momentum Profits Based on Structural Models

	1 Month/6 Month			6 Month/6 Month		
	CAPM risk-adjusted			CAPM risk-adjusted		
	All	Jan	Non-Jan	All	Jan	Non-Jan
Winner	0.0063	0.021	0.0053	0.0067	0.0137	0.0061
	(2.93)	(2.99)	(2.60)	(3.22)	(1.94)	(2.97)
Loser	0.0027	0.0253	0.0011	0.0014	0.0293	-0.0012
	(1.33)	(2.45)	(0.54)	(0.60)	(2.12)	(-0.50)
W-L	0.0036	-0.0043	0.0042	0.0053	-0.0156	0.0072
	(3.68)	(-0.66)	(3.45)	(3.19)	(-1.11)	(3.67)
	Three-factor Model risk-adjusted			Three-factor Model risk-adjusted		
	All	Jan	Non-Jan	All	Jan	Non-Jan
Winner	0.0076	0.0142	0.0070	0.0081	0.0079	0.0081
	(8.02)	(7.07)	(6.96)	(6.91)	(2.07)	(6.42)
Loser	0.0036	0.0197	0.0023	0.0017	0.0232	-0.0003
	(2.63)	(2.78)	(1.91)	(0.93)	(1.99)	(-0.16)
W-L	0.0040	-0.0055	0.0047	0.0064	-0.0153	0.0083
	(2.84)	(-0.78)	(3.70)	(2.83)	(-1.04)	(4.08)

To calculate CAPM risk-adjusted profits, the momentum profit is regressed on a constant and the excess market return,

$$WML_t = \alpha - \beta EM_t + \varepsilon_t$$

where WML_t is the momentum profit from the winner-minus-loser portfolio in month t, EM_t is the excess market return in month t, and ε_{it} is the disturbance. The risk-adjusted profits (WML_t^{adj}) are

$$WML_t^{adj} = WML_t - \hat{\beta} EM_t$$

where $\hat{\beta}$ is the estimated CAPM beta. One can also adjust the risk by the Fama-French three factor model in the same fashion.

However, as Conrad and Kaul (1998) among others suggest that using structural asset pricing models as in many studies results in a joint test of the validity of the structural model for what constitutes relevant risk factors and the validity of the hypothesis that momentum is due to risk. If any such structural model has specification error or does not account for all risk factors, test results based on the model will be unreliable. We therefore employ an alternative approach proposed by Du and Watkins (2007) to study the sources of momentum profits.

3.2 Sources of Momentum Profits Based on Du and Watkins (2007)

If expected returns are assumed to be constant (as in Conrad and Kaul, 1998), sample unconditional mean returns become an unbiased estimator of true expected returns of stocks, and the three components of momentum (i.e. dispersion in unconditional mean returns, serial correlation and cross-serial correlation) are closed tight to alternative explanations of momentum. More specifically, if momentum is mainly due to risk or dispersion in expected returns, the dispersion in unconditional mean returns should explain all of observed momentum profits; on the other hand, if momentum is chiefly due to behavioral biases suggested by LM, BSV, DHS and HS, cross-serial correlation or serial correlation (or both) should explain momentum profits. Therefore, if expected returns are constant, a decomposition of momentum profits into these three components can shed considerable light on the validity of alternative explanations.

LM propose a decomposition methodology. But their decomposition not only may be biased (as Jegadeesh and Titman (2002) show), but also is not applicable to the popular decile-based momentum strategy (i.e. the Jegadeesh and Titman (1993) strategy). Therefore, Du and Watkins (2007) propose an alternative decomposition method, which is not only unbiased but also applicable to the decile-based strategy. Their discussion is based on the long-horizon momentum strategy studied by Jegadeesh and Titman (1993). Since we also consider the short-horizon momentum investigated by Gutierrez and Kelley (2008) in this paper, we generalize their discussion along the same line. That is, we first analytically determine the sources of momentum profits by considering the Lo and MacKinlay (1990) strategy. Based on the insight from the analysis, we implement a regression-based approach to decompose the momentum profits from the decile-based momentum strategy.

We consider a general momentum strategy with a ranking period of *k* months and a holding period of *l* months. The momentum portfolio in any month *t* consists of *l* zero-investment portfolios formed over *t*-k to *t*-1, *t*-1-k to *t*-2, …, and *t*-l-k-1 to *t*-l. Let's focus on the zero-investment portfolio formed over *t*-k to *t*-1 based on the Lo and MacKinlay (1990) strategy.[8] Its profit in month t, $\pi_t^{t-1,t-k}$ is

$$\pi_t^{t-1,t-k} = \frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1}^k - r_{m,t-1}^k)r_{i,t}$$

$$= \frac{1}{N}\sum_{i=1}^{N} r_{i,t-1}^k r_{i,t} - r_{m,t-1}^k r_{m,t} \tag{2}$$

with *N* is the number of assets in the market, $r_{i,t-1}^k$ is the cumulative return of asset *i* from month *t* – k to *t* -1, $r_{m,t-1}^k$ is the cumulative return on the equal-weighted index from month *t* – k to *t* -1, and $r_{i,t}$ is the return of asset *i* in month *t*.

It is easy to show that the expected profit, $E(\pi_t^{t-1,t-k})$ is

$$E(\pi_t^{t-1,t-k}) = \frac{1}{N}\sum_{i=1}^{N} E(r_{i,t-1}^k r_{i,t}) - E(r_{m,t-1}^k r_{m,t})$$

[8] The same logic applies to the other portfolios. The return of the momentum portfolio is the simple average of the returns of these l portfolios.

$$= \frac{N-1}{N^2}\sum_{i=1}^{N}\text{cov}(r_{i,t-1}^k, r_{i,t}) - [\text{cov}(r_{m,t-1}^k, r_{m,t}) - \frac{1}{N^2}\sum_{i=1}^{N}\text{cov}(r_{i,t-1}^k, r_{i,t})] + \frac{k}{N}\sum_{i=1}^{N}(\mu_i - \mu_m)^2$$

$$= O - C + \sigma^2(\mu) \qquad (3)$$

where μ_i and μ_m are the monthly unconditional means of asset i and the equal-weighted index. Equation (3) shows that there are three sources of momentum profits: (1) positive autocovariances between the month-t return and the lagged k-month return (O), (2) negative cross-serial covariances at the same horizon (C), and (3) the dispersion of the mean returns ($\sigma^2(\mu)$). Again, if expected returns are assumed to be time invariant, these three components are closed tight to alternative explanations of momentum. Therefore, a decomposition of momentum profits into these three components can shed considerable light on the validity of alternative explanations.

As Du and Watkins (2007) point out, since the Lo and MacKinlay (1990) and the Jegadeesh and Titman (1993) strategies are closely related, the monthly profit of the Jegadeesh and Titman (1993) strategy based on the same past k-month return should also depend on (1) positive autocovariances between the month-t return and the lagged k-month return, (2) negative cross-serial covariances at the same horizon, and (3) the dispersion of the mean returns.

Let's now consider the expected profit in month *t* from the Jegadeesh and Titman (1993) strategy, $E(WML_t)$.

$$E(WML_t) = E[\frac{1}{n}(\sum_{i=1}^{n} r_{i,t}^W - \sum_{i=1}^{n} r_{i,t}^L)] \qquad (4)$$

where *n* is the number of winners (losers) in each month, $r_{i,t}^W$ is the return of a winner asset in the investment period, and $r_{i,t}^L$ is the return of a loser asset in the investment period. Du and Watkins (2007) argue that although it is difficult to directly decompose the expected portfolio return into the three relevant components (i.e. dispersion in unconditional means, serial correlation, and cross-serial correlation), one may still do so indirectly by decomposing asset returns into the corresponding three components.

Consider the following regression model,

$$r_{i,t} = \mu_i + \rho_i r_{i,t-1}^k + \varepsilon_{i,t} \qquad (5)$$

with $r_{i,t}$ the return of asset *i* in month *t*, μ_i is the unconditional mean of asset i, ${}_i r_{i,t-1}^k$ is the cumulative return of asset i from month t–k to t–1, ρ_i is the autocorrelation coefficient between the month-t return and the lagged k-month return, and $\varepsilon_{i,t}$ is a zero-mean disturbance term. $\varepsilon_{i,t}$ is net of the effects of the unconditional mean and autocovariances between the month-t return and the lagged k-month return.

Therefore, as Du and Watkins (2007) point out, if $\varepsilon_{i,t}$ can generate momentum profits, it must be due to the cross-serial covariances among assets that are not included in the model but included in the return. Hence, the asset return may be viewed as having three components for the purposes of momentum profit decomposition:

$$r_{i,t} = \mu_i + O_{i,t} + C_{i,t} \tag{6}$$

where $O_{i,t} = \rho_i r_{i,t-1}^{6}$, and $C_{i,t} = \varepsilon_{i.t} \quad O_{i,t}$ is the return component due to the autocovariances. $C_{i,t}$ is the return component due to the cross-serial covariances among assets.

It is then easy to decompose momentum profits from the Jegadeesh and Titman (1993) strategy into three relevant components.

$$\begin{aligned}
E(WML_t) &= E[\frac{1}{n}(\sum_{i=1}^{n} r_{i,t}^{W} - \sum_{i=1}^{n} r_{i,t}^{L})] \\
&= E\{\frac{1}{n}[\sum_{i=1}^{n}(\mu_i^W + O_{i,t}^W + C_{i,t}^W) - \sum_{i=1}^{n}(\mu_i^L + O_{i,t}^L + C_{i,t}^L)]\} \\
&= E[\frac{1}{n}(\sum_{i=1}^{n}\mu_i^W - \sum_{i=1}^{n}\mu_i^L) + \frac{1}{n}(\sum_{i=1}^{n} O_{i,t}^W - \sum_{i=1}^{n} O_{i,t}^L) + \frac{1}{n}(\sum_{i=1}^{n} C_{i,t}^W - \sum_{i=1}^{n} C_{i,t}^L)] \\
&= \mu + O + C
\end{aligned} \tag{7}$$

where $\mu = E[\frac{1}{n}(\sum_{i=1}^{n}\mu_i^W - \sum_{i=1}^{n}\mu_i^L)]$, $O = E[\frac{1}{n}(\sum_{i=1}^{n} O_{i,t}^W - \sum_{i=1}^{n} O_{i,t}^L)]$, and $C = E[\frac{1}{n}(\sum_{i=1}^{n} C_{i,t}^W - \sum_{i=1}^{n} C_{i,t}^L)]$. The first component, μ, is due to dispersion in unconditional means. The second component, *O*, is due to serial correlations in returns. The last component, *C*, is due to cross-serial correlations among securities.

By comparing Equations (7) and (3), it is easy to see that the advantage of the Du and Watkins (2007) approach compared to the Lo and MacKinlay (1990) decomposition methodology is that it only requires that the expected return estimator be unbiased and does not require that the cross-sectional variance of sample mean returns be an unbiased estimator of the cross-sectional variance of true expected returns. Therefore, it enables an unbiased decomposition of momentum profits into three relevant components.

Empirically, following Du and Watkins (2007), we estimate Equation (5) by OLS and obtain the estimates for the three components of asset returns and momentum profits. We emphasize that we estimate Equation (5) with the entire sample not the truncate sample (that excludes the ranking and holding periods as in Jegadeesh and Titman, 2002). This ensures that our expected return estimates are unbiased. We also stress again that it is important to further decompose the component due to time-series dependence into the component due to serial correlation and that due to cross-serial correlation, because otherwise we will underestimate the importance of time-serial dependence if the serial correlation component has opposite sign from the cross-serial correlation component.

3.2 Empirical Results

Table 3 reports the mean momentum profits as well as its three sources. The t-ratios are based on Newey-West HAC standard errors with the lag parameter set equal to 12 (or one year). The section headed by "1 Month/6 Month" shows the sources of the short-horizon momentum profits. As we can see, the dispersion in expected returns (μ) is a statistically and economically important factor of the short-horizon momentum if we estimate mean returns with the entire sample not the truncated sample. μ is equal to 0.0028 with a t-statistic of 3.14. It explains about 88% of the short-horizon momentum. The serial covariance component (*O*) is significantly negative, while the cross-serial covariance component (*C*) is significantly positive. *O* is equal to -0.0026 with a t-statistic of -2.77, where *C* is 0.0030 with a t-statistic of 3.22. Therefore, if we did not further decompose the component due to time-series dependence into the component due to serial correlation and that due to cross-serial correlation, we could significantly underestimate the importance of time-serial dependence.

Table 3. Sources of Momentum Based on a Reduced-Form Approach

	1 Month/6 Month	6 Month/6 Month
WML	0.0032 (3.04)	0.0051 (2.75)
μ	0.0028 (3.14)	0.0063 (6.48)
O	-0.0026 (-2.77)	-0.0052 (-4.50)
C	0.0030 (3.22)	0.0041 (2.57)

μ is the component due to cross-sectional dispersion in unconditional means. *O* is the component due to serial correlations in returns. *C*, is the component due to cross-serial correlations among securities.

The section headed by "6 Month/6 Month" shows the sources of the long-horizon momentum profits. Again, the dispersion in expected returns (μ) is a statistically and economically important factor of the long-horizon momentum as long as we estimate mean returns with the entire sample. μ is equal to 0.0063 with a t-statistic of 6.48. It explains about 124% of the long-horizon momentum. Again, the serial covariance component (*O*) is significantly negative, while the cross-serial covariance component (*C*) is significantly positive. *O* is equal to -0.0052 with a t-statistic of -4.50, where *C* is 0.0041 with a t-statistic of 2.57. Therefore, again, if we did not further decompose the component due to time-series dependence into the component due to serial correlation and that due to cross-serial correlation, we could significantly underestimate the importance of time-serial dependence.

Therefore, for both momentum strategies, as soon as we estimate unconditional mean returns with the whole sample not the truncated sample, we find that dispersion in unconditional mean returns is statistically and economically important to explain momentum profits. This finding is consistent with Bulkley and Nawosah (2009), which suggests that the conclusion in Jegadeesh and Titman (2002) may be open to question in that momentum may be partly due to risk. We also find that, for both momentum strategies, the serial correlation component has opposite sign from the cross-serial correlation component. As a result, the time-series component as a whole explains very little momentum profits. Given that both components due to time-series dependence are significant, the conclusion in Bulkley and Nawosah (2009) may also be open to question in that momentum may be partially due to behavioral biases. Therefore, our findings suggest that momentum may have multiple sources. Risk or behavioral biases in isolation may not be sufficient to explain momentum.

4. Conclusion

Lo and MacKinlay (1990) suggest that there are three sources of momentum profits: (positive) serial correlation, (negative) cross-serial correlation, and dispersion in unconditional mean returns. Conrad and Kaul (1998) indicate that if expected returns are constant over time, these three momentum components will be closed tight to alternative explanations of momentum. Specifically, if momentum is due to risk, dispersion in unconditional mean returns should explain momentum; on the other hand, if momentum is due to behavioral biases, momentum should be mainly explained by cross-serial correlation or serial correlation.

Bulkley and Nawosah (2009) recently find that momentum in individual stock returns is mainly explained by dispersion in unconditional mean returns, which suggests a risk-based explanation for momentum. However, they do not decompose the momentum component due to time-series dependence into the component due to serial correlation and that due to cross-serial correlation. Therefore, their approach may underestimate the importance of time-serial dependence if the serial correlation component has opposite sign from the cross-serial correlation component. Motivated by this observation, we apply the Du and Watkins (2007) methodology, which enables an unbiased decomposition of momentum profits into three relevant components (i.e. dispersion in unconditional mean returns, serial correlation and cross-serial correlation).

Empirically, we focus on two commonly studied momentum strategies for robustness. One is the long-horizon momentum investigated by Jegadeesh and Titman (1993), while the other is the short-horizon momentum recently studied by Gutierrez and Kelley (2008). For both momentum strategies, we find that dispersion in unconditional mean returns is statistically and economically important to explain momentum profits. Furthermore, for both momentum strategies, we also find that the serial correlation component has opposite sign from the cross-serial correlation component. As a result, the time-series component as a whole explains very little momentum profits. However, since both components due to time-series dependence are significant, momentum may at least partially due to time-series dependence. Therefore, different from Bulkley and Nawosah (2009), our findings suggest that momentum has multiple sources and risk or behavioral biases in isolation may not be sufficient to explain momentum.

References

Balvers, R. J., & Wu, Y. (2006). Momentum and mean reversion across national equity markets. *Journal of Empirical Finance* 13, 24-48.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics 49*, 307-343.

Bulkley, G., & Nawosah, V. (2009). Can the Cross-Sectional Variation in Expected Stock Returns Explain Momentum?, *Journal of Financial and Quantitative Analysis* 44, 777-794.

Chan, L. K. C., Hameed, A., & Tong, W. (2000). Profitability of Momentum Strategies in the International Equity Markets. *Journal of Financial and Quantitative Analysis 35*, 153-172.

Chordia, T., & Shivakumar, A. (2002). Momentum, business cycle and time-varying expected returns. *Journal of Finance* 57, 985-1019

Conrad, J., and G. Kaul, 1998, "An Anatomy of Trading Strategies," *Review of Financial Studies*, 11, 489-519.

Cooper, M. J., R. C. Gutierrez, and A. Hameed, 2004, "Market States and Momentum," *Journal of Finance*, 59, 1345-1365.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998) Investor psychology and security market under- and over-reaction. *Journal of Finance 53*, 1839-1886.

Du, D. & Watkins, B. (2007). When competing momentum hypotheses really do not compete: How the sources of momentum profits change through time. *Journal of Economics and Business*, 59, 130-143.

Fama, E. F., & French, K. R, (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51, 55-84.

Griffin, J. M., Ji, S., & Martin, J. S. (2003). Momentum investing and business cycle risk: evidence from pole to pole. *Journal of Finance* 58, 2515-47.

Grundy, B., & Martin, J. S. (2001). Understanding the nature and the risks and the sources of the rewards to momentum investing. *Review of Financial Studies* 14, 29-78.

Gutierrez, R. & E. Kelley, (2008), The Long-Lasting Momentum in Weekly Returns, *Journal of Finance* 61, 415-447.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance 54*, 2143-2184.

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance* 55, 265-95.

Hvidkjaer, S. (2006), A Trade-Based Analysis of Momentum, *Review of Financial. Studies* 19, 457 - 491.

Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. *Journal of Finance*, 45, 881-898.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance 48*, 65-91.

Jegadeesh, N., & Titman, S. (2001). Profitability of momentum strategies: an evaluation of alternative explanations. *Journal of Finance 56*, 699-720

Jegadeesh, N., & Titman, S. (2002). Cross-sectional and time-series determinants of momentum returns. *Review of Financial Studies* 15, 143-157.

Lee, C., & Swaminathan, B. (2000). Price momentum and trading volume. *Journal of Finance* 55, 2017–2070.

Lehmann, B. N., 1990, “Fads, Martingales, and Market Efficiency,” *Quarterly Journal of Economics*, 105, 1-28.

Lewellen, J. (2002). Momentum and autocorrelation in stock returns. *Review of Financial Studies 15*, 533 – 564.

Lo, A. W., and A. C. MacKinlay, 1990, “When Are Contrarian Profits Due to Stock Market Overreaction?,” *Review of Financial Studies*, 3, 175-205.

Moskowitz, T. J., & Grinblatt, M. (1999). Do industries explain momentum?. *Journal of Finance 54*, 1249 – 1290.

Rouwenhorst, K. G. (1998). International momentum strategies. *Journal of Finance 53*, 267-284.