Momentum in Canadian Stock Returns

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Abstract
Empirical evidence suggests that U.S. and Canadian stock returns follow predictable patterns over a short-term horizon. In particular, abnormal profits could have been generated by purchasing previous strong performers and selling previous poor performers. Our evidence suggests that a portion of this profitability represents appropriate compensation for risk and risk premiums that vary through time. We also examine the impact of transactions costs on the implementation of this strategy and find it may not be exploitable by the average retail investor facing higher levels of transactions costs. However, sensitivity analysis indicates that momentum trading may have merit for more nimble traders facing lower transactions costs.

Résumé
Les données empiriques suggèrent que le rendement sur les actions aux États-Unis et au Canada se conforme, à court terme, à des modèles prévisibles. En particulier, des profits anormaux auraient pu être générés par l'achat d'anciens performateurs forts et la vente d'anciens performateurs faibles. Nos données suggèrent qu'une partie de cette rentabilité représente une compensation appropriée au risque et aux primes de risque qui varient avec le temps. Nous examinons aussi l'impact des frais de transaction sur la mise en pratique de cette stratégie, et nous trouvons que l'investisseur individuel moyen contraint à faire face à des frais de transaction plus élevés ne serait peut-être pas en mesure de l'exploiter. Cependant, l'analyse de susceptibilité indique que la stratégie de placement par "momentum" aurait peut-être de la valeur pour des investisseurs plus agiles confrontés à des frais de transaction moins élevés.

There is extensive literature examining the performance of technical trading strategies, which attempt to identify and exploit recurring patterns in stock market return series through time. DeBondt and Thaler (1985) and subsequent studies provided evidence on the profitability of 3- to 5-year contrarian strategies, which involve buying past poor performers and selling past strong performers. Brock, Lakonishik, and LeBaron (1992) used 90 years of daily data (1897-1986) on the Dow-Jones Industrial Average to show that moving average and trading range break-out strategies produce superior returns. It is difficult to provide satisfactory justification for these strategies at an intuitive level. Malkiel (1981) went so far as to suggest that "technical analysis is anathema to the academic world." (p. 116) Certainly, if we accept the general notion that security markets are efficient, then security prices at a given point in time should reflect the relevant information available at that time. Hence prices should change due to the arrival of new information, which by its very nature is unpredictable. Despite the apparent lack of theoretical foundation, we observe that most security analysts provide a substantial amount of technical information to support their recommendations.

In this paper, we examine one such technical strategy that appears to generate abnormal returns according to recent empirical evidence. Several studies indicate that forming portfolios based on a price-momentum model by buying stocks that have performed well in the recent past and selling those that have performed poorly have outperformed the equity market as a whole. Jegadeesh and Titman (1993) examined New York and American stock exchange data over the past 3 decades using all available common stock returns on the Center for Research in Security Prices (CRSP) data file. Their momentum-based strategy generated significant excess

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returns, even after controlling for systematic risk. The existence of this pattern in U.S. stock returns is confirmed by Chan, Jegadeesh, and Lakonishok (1996) and by Karolyi and Kho (1996).

Foerster, Prihar, and Schmitz (1994/1995) followed a similar strategy to Jegadeesh and Titman (1993) using Canadian data from 1978 to 1993 and documented even stronger evidence of momentum in stock returns. Subsequent Canadian studies by Kan and Kirikos (1996), and Korkie and Plas (1995) supported the profitability of momentum-based trading strategies. While these results may be surprising to financial economists, they substantiate an old market motto: "The trend is your friend." These sentiments were echoed recently by John Silva, chief economist at Kemper Financial Services of Chicago, who stated "financial markets are driven by expectations and not the real world" (Jorgenson, 1995, p. 13). Silva went on to note that North American traders are momentum players.

This study uses Canadian data to evaluate alternative explanations for the existence of this phenomenon. Summary statistics provided in the next section support the notion that Canadian stock returns do in fact exhibit a short-term momentum property. Traditional measures of risk, including standard deviation of returns and unconditional market betas, are not able to account for the observed return phenomenon, and we also reject the hypothesis that the results are significantly related to firm size. We generate artificial individual series returns using a bootstrap methodology to determine if these results could, in fact, be consistent with a random walk model of stock returns. Our evidence rejects this hypothesis, which is consistent with the U.S. evidence offered by Karolyi and Kho (1996).

Karolyi and Kho (1996) provided evidence that momentum in U.S stock returns could represent appropriate compensation for risk and risk premiums that vary through time. The third section examines this possibility using a conditional equilibrium asset pricing model that accounts for a portion of the excess returns by allowing variation in risk measures and risk premiums through time. However, this asset pricing model is unable to account for the entire magnitude of the abnormal profits in the raw return series. We do not speculate here as to the cause of this pattern in returns. However, it may be attributable to market sentiment, or to a market "that responds only gradually to new information," as is argued by Chan et al. (1996, p. 1681).

The existence of this pattern leads to the obvious question: "Is it exploitable?" If it is, then it should have disappeared long ago. However, it has persisted through the years despite the fact that it is widely recognized by investors and that relative strength technical indicators are available to the public. This suggests that, despite its relevance, momentum may not be exploitable by investors. As with any active trading strategy, one would expect transactions costs to have a substantial impact on profitability, and we examine this possibility. We demonstrate that transactions costs (i.e., commission fees plus bid-ask spread) eliminate the excess returns generated by our trading strategy for the typical retail investor. However, momentum trading could produce above-average investment performance for institutional investors facing minimal trading costs. We offer concluding remarks in the final section.

The Momentum Phenomenon

The Profitability of Momentum Trading

We follow the basic approach of Foerster et al. (1994/1995), who rebalanced their portfolios quarterly using a weighting scheme that considered the four previous quarterly returns, with the most recent quarterly return being weighted twice as heavily as the others. Foerster et al.'s sample selection was substantially different from that of Jegadeesh and Titman (1993). Foerster et al. chose stocks included in the TSE 100 Index at the end of 1993, based on the rationale that this index "best represents the stocks contained in Canadian institutional portfolios." (p. 10) They acknowledged that this sample selection introduces survivorship bias, since firms included in the TSE 100 at the end of 1993 would be those that fared well in previous years.[1]

Our sample consisted of 238 TSE/Western database firms whose market capitalization exceeded $40 million at the beginning of our sample period (January 1978). This approach captures larger stocks that may be of primary interest to institutional investors and avoids survivorship bias, since it does not preclude the selection of firms that do not survive our sample period. We replicated the basic results of Foester et al. for our sample, using a slightly different sample period (January 1978 to December 1990), because of data limitations. Ten portfolios, each with an equal number of stocks, were formed and labelled P1 (worst past performer) through P10 (best past performer). Following the approach of DeBondt and Thaler (1985), Jegadeesh and Titman (1993), and Karolyi and Kho (1996), we included a category to allow for returns on a zero-cost portfolio that could be constructed by simultaneously buying the P10 portfolio and selling the P1 portfolio (referred to as P10-P1).[2]

Summary statistics presented in Table 1 confirm the Foerster et al. (1994/1995) results, although their momentum property was not as strong in our sample. The sample quarterly average return ($\bar{r}_q$) for the P10 portfolio over the period was 5.87%, with a quarterly

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Table 1
Returns of Relative Strength Portfolios (January 1979 - December 1990)

The relative strength portfolios are formed based on the past four quarterly returns (with double weight being given to the most recent quarterly return). The stocks are ranked in ascending order and 10 equally weighted portfolios are formed. P1 represents the stocks with the weakest past performance, while P10 represents those stocks with the strongest past performance. P10-P1 refers to an investment strategy in which the stocks in the lowest ranking portfolio are sold short and the stocks in the highest ranking portfolio are purchased. The performance numbers are also provided for our market proxy (the TSE 300 Total Return Index) and the riskfree asset (1-month Government of Canada treasury bill yields).

	Stocks split into 10 equal portfolios[a]												
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1[b]	TSE 300	Risk-free
Mean return (%)	1.77	2.69	2.50	3.30	4.16	4.35	4.43	3.42	3.04	5.87	4.10	3.31	2.78
Volatility (std) (%)	12.5	10.3	10.5	8.91	9.84	9.42	9.27	9.59	9.50	11.30	11.26	9.38	0.78
β	1.032	0.919	0.962	0.857	0.962	0.952	0.915	0.950	0.886	1.018	-0.016	1.000	0
Average size (millions)	353.7	320.8	342.5	292.9	275.5	286.0	288.3	293.3	282.0	273.0	-80.7	n/a	n/a
Sharpe ratio	-0.081	-0.009	-0.027	0.058	0.140	0.166	0.178	0.066	0.027	0.275	0.364	0.057	0
Treynor ratio	-0.010	-0.001	-0.003	0.006	0.014	0.016	0.018	0.007	0.030	0.030	-2.513	0.005	n/a
α	-0.016	-0.006	-0.008	0.001	0.009	0.011	0.012	0.001	-0.002	0.026	0.041	0	0
Skewness	0.139	0.409	-0.112	-0.13	-0.345	-0.621	-0.317	-0.182	-0.354	-0.284	1.048	-0.377	1.134
Kurtosis	2.558	3.034	2.575	3.228	4.256	2.985	2.800	3.024	2.638	2.715	5.742	3.377	3.757
Average share price ($)	23.65	25.32	26.50	24.48	25.97	25.17	26.74	26.91	25.81	29.24	26.45	n/a	n/a
Median share price ($)	19.50	19.94	19.13	20.00	20.50	20.63	20.25	20.13	20.63	20.00	19.82	n/a	n/a

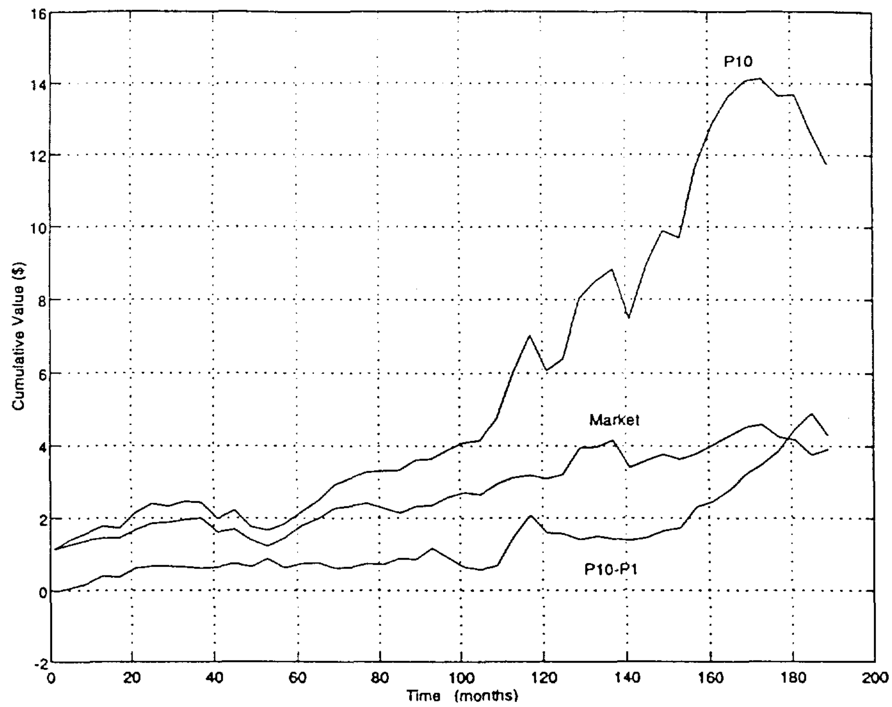
[a]In any given quarter there are the same number of stocks in each of the 10 portfolios. However, due to missing data, the number of stocks in each portfolio may be different from one quarter to the next. For example, in the first portfolio formation quarter there are 20 stocks in each portfolio, while in the last quarter there are only 12 stocks in each portfolio.
[b]Since P10-P1 is a self financing portfolio, it provides only a risk premium (not a riskless return plus a risk premium). Therefore, we use total return and not excess return above the risk-free rate when calculating the Sharpe, Treynor and alpha performance measures for P10-P1.

standard deviation (σ_p) of 11.3%; the P1 portfolio $\overline{r_q}$ was 1.77%, with a σ_p of 12.5%; and the P10-P1 portfolio $\overline{r_q}$ was 4.10%, with a σ_p of 11.26%. During the same time period, the quarterly return for the TSE 300 was 3.31%, with a standard deviation of 9.38%, while the yield on 1-month Government of Canada treasury bills averaged 2.78%. Figure 1 shows the cumulative wealth effect of investing in P10, P10-P1, and the TSE 300 Index over the sample period. It highlights the magnitude and persistence of the momentum property. In fact, P10 offers an annual return above the market return in 10 of the 13 years, and it only underperforms the market in 1981 (by 1.2%), 1988 (by 0.3%), and 1990 (by 6.9%). Overall, a 1978 dollar would have grown to $11.74 by 1990 if invested in P10, versus $3.91 if invested in the TSE 300. The line representing P10-P1 indicates that investing $1 in P10, which is financed by short selling one dollar's worth of P1 (for a net investment of zero), would have produced $4.29 by the end of 1990.

Traditional Performance Measures

We include Sharpe ratios, Treynor ratios, and Jensen's alphas in Table 1, which are three traditional measures of portfolio performance. These risk-adjusted criteria confirm the superior performance of the portfolios with higher return momentum.[3] The Sharpe ratio for the P10 portfolio is much greater than for portfolios P1 through P9 and is approximately five times the size of the TSE 300 Sharpe ratio. P10 has a Treynor ratio that is

Figure 1.
The Cumulative Value of One Dollar Invested in Momentum Portfolio(s) versus the Market Index.



roughly six times that of the TSE 300 and a large positive Jensen's alpha value. At the opposite end of the momentum spectrum, P1 has negative values for all three performance measures. It underperforms all other portfolios and the TSE 300 based on these criteria.

The P10-P1 portfolio has a negative beta that is very close to zero. The implication is that the P10-P1 portfolio has very little systematic risk. This can be attributed to the fact that during market downturns, the P1 portfolio returns tend to fall faster than the P10 portfolio returns, which reduces the portfolio's sensitivity to market swings. The expected return on this zero-cost, zero-risk portfolio should be zero in perfect capital markets to preclude arbitrage. However, we observe a 4.10% quarterly return for P10-P1, which produces a positive alpha of 0.041, by far the largest alpha in Table 1.[4] The P10-P1 Sharpe ratio of 0.364 is roughly nine times that of the TSE 300 and suggests superior performance relative to total portfolio risk. In addition, the skewness statistic is large and positive for the P10-P1 portfolio, while it is negative for the TSE 300 and most of the other portfolios. Since risk averse investors will prefer positively skewed distributions to negatively skewed ones, P10-P1 is attractive based on this statistic.

Tests for Size Effects

There is a large body of empirical evidence, from Banz (1981) to Fama and French (1992), that suggests that firm size is related to expected returns. We examine the possibility that firm size, as measured by market capitalization, may impact our results. Table 1 reports average firm size for each of our selected portfolios, which appear to be reasonably close across our portfolios. We perform two tests to detect the presence of any size effects in our portfolio returns, focussing on the difference between the sizes of our extreme portfolios (P10 and P1). The first test is a standard *t*-statistic that tests whether the average size differential between P10 and P1 is significantly different than 0. The calculated value of –3.260 suggests there is a significant difference in the average size of the P10 and P1 portfolios. We then test whether the estimated coefficient in the regression of return differential (P10-P1) on the logarithm of the ratio of firm sizes is significantly different from zero using another *t*-statistic.[5] The *t*-statistic for this test is 0.306, which suggests there is no significant relationship between market capitalization and portfolio return performance.

Table 2
Bootstrap Tests for Random Walk Model

The residual series generated for each stock from the Random Walk Model (given below) is sampled with replacement to obtain a simulated returns series.

$$R_{i,t} = E[R_i]+\epsilon_{i,t}$$

The portfolio selection strategy is applied to each set of new returns. The mean returns for the simulated portfolios are then averaged across the 500 simulations. P1 denotes the portfolio of lowest past-return stocks and P10 the portfolio of highest past return stocks. The empirical p-value denotes the proportion of the time the simulated mean return is larger than the actual mean return for a given portfolio.

		Simulations	
	Actual return (%)	Return (%)	Empirical p-value
P1	1.77	2.68	0.666
P2	2.69	3.57	0.650
P3	2.50	3.72	0.780
P4	3.30	3.91	0.540
P5	4.16	4.02	0.414
P6	4.35	4.09	0.352
P7	4.43	4.19	0.392
P8	3.42	4.31	0.720
P9	3.04	4.37	0.798
P10	5.87	4.49	0.194
P10-P1	4.10	1.81	0.096

Random Walk Simulation Evidence

We conclude this section by employing a bootstrap methodology to determine whether the results could be consistent with a simple random walk model of stock returns. Bootstrapping allows us to generate empirical distributions from models that account for the attributes of stock returns. We are able to generate hundreds of simulated return series for individual stocks using the equilibrium returns-generating model under consideration, which can then be compared to the actual stock return series.

We begin by assuming the expected return on an individual stock is the same at any given point in time, and we use the average return to proxy this expected return. Formally, we have $R_{it} = \overline{R_i} + \epsilon_{it}$, where R_{it} is the actual return on stock i at time t, $\overline{R_i}$ is the average return on security i throughout the entire time period, and ϵ_{it} is the resulting residual. We use this format to generate a series of residuals that are assumed to be independent and identically distributed. The estimated residuals are then drawn with replacement to form a scrambled series of residuals through the use of a random number generation technique. The scrambled residuals are used to reconstruct simulated returns data for each stock. This procedure is repeated 500 times for each security in order to generate a large distribution of returns. We then determine the portfolio returns generated when our portfolio formation strategy is implemented to form 10 momentum portfolios based on each of the simulated return series.

The averages of these simulated returns for each portfolio are reported in Table 2 along with the actual returns previously reported in Table 1. Empirical p-values are reported that indicate the proportion of simulated portfolio returns that exceed those in the actual data. Thus we would expect to observe empirical p-values close to 0.50 (i.e., the median of the simulation results), if the actual returns were truly following a random walk process. Empirical p-values below (above) 0.50 indicate the observed return is well above (below) the simulated median, which suggests the observed high (low) return is unlikely to be a random occurrence. The empirical p-value of 0.6660 for P1 indicates 66.60% (or 333 out of 500) of the simulated returns for P1 exceeded the actual average return of 1.77%. This confirms the tendency in the actual return series for poor past performance to persist. Similarly, the empirical p-values of 0.1940 and 0.0960 for P10 and P10-P1 indicate a tendency in the actual data for strong past performance to persist. Overall, we observe a pattern of low empirical p-values for the good portfolios and high values for the poor portfolios in Table 2. This supports the notion that a random walk model cannot account for the profitability of the momentum-based trading strategy.

Time-Varying Risk and Momentum

Estimation Procedure

Karolyi and Kho (1996) provided evidence that momentum in U.S stock returns could represent appropriate compensation for risk and risk premiums that vary through time. The existence of time variation in risk and risk premiums in stock returns is supported in the literature. Ferson (1989) noted that recent evidence of return predictability "has stimulated the use of asset pricing models with time-varying expected returns." (p. 1191) Indeed, there is widespread evidence of variation in covariances from several authors, such as Bollerslev, Engle, and Woolridge (1988), Ferson (1989), Ferson, Kandal, and Stambaugh (1987), Harvey (1989), and Ng (1991). Several studies also provided evidence of time variation in risk premiums, such as Campbell (1987), Fama and French (1988a, 1988b, 1989), Fama and Schwert (1977), Harvey (1989), Keim and Stambaugh (1986), and Ng (1991).

We allow time variation in expected returns by estimating conditional covariances with a market index similar to Bodurtha and Mark (1991), Bollerslev et al. (1988), Harvey (1989), Ng (1991), and Shanken (1990). We use the following system of equations, which follows closely the specification used by McCurdy and Morgan (1992) for currency futures returns:

$$R_{it} - r_{ft} = \gamma_{0i} + \frac{h_{iMkt,t}}{h_{Mkt,t}}(\gamma'_{Mkt}Z_{t-1}) + \epsilon_{it}, \quad (1)$$

$$R_{Mkt,t} - r_{ft} = \gamma'_{Mkt}Z_{t-1} + \epsilon_{Mkt,t,} \text{ where}, \quad (2)$$

$$\epsilon_t \,|\, \Omega_{t-1} \sim N(0,H_t). \quad (3)$$

In this framework, $R_{it} - r_{ft}$ is the excess returns for security i at time t, $R_{Mkt,t} - r_{ft}$ is the excess returns for the market portfolio (the TSE 300 Composite Index) at time t; the γ variables represent parameters to be estimated; the vector Z_{t-1} is a subset of the total information set available at t-1; and ϵ_t is the error term vector, which is assumed to be conditionally normally distributed with a covariance matrix denoted as H_t. Z_{t-1} consists of a set of instruments shown in a number of studies to predict excess market returns. It includes a constant, the 1-month Government of Canada treasury bill yield (r_f); the term spread between the yields on 10-year Government of Canada bonds and 1-month treasury bills (TERM); the spread between the yields of long-term Government of Canada bonds and long-term Canadian corporate bonds (DEFAULT); the 12-month lagged dividend yield on the TSE 300 Index (DY); the conditional variance of market returns ($h_{Mkt,t-1}$); and a January dummy.[6]

The conditional covariance matrix (H_t) is represented as:

$$H_t = \begin{bmatrix} h_{it} & h_{iMkt,t} \\ h_{iMkt,t} & h_{Mkt,t} \end{bmatrix} = D_tRD_t \quad (4)$$

where D_t is the diagonal matrix of conditional standard deviations ($\sqrt{(h_{i,t})}$) along the diagonal and R is the matrix of constant unconditional correlations (ρ_{ij}) estimated across the sample. The conditional variance terms (h_{it}) are estimated using the following GARCH(1,1) specification: $h_{it} = a_i + b_i\epsilon_{i,t-1}^2 + c_ih_{i,t-1}$. The nondiagonal conditional covariance terms ($\omega_{ij,t}$) of H_t are estimated using $\omega_{ij,t} = \rho_{ij}\sqrt{h_{i,t}}\sqrt{h_{j,t}}$, which is similar to the approach used by Ng (1991), Schwert and Seguin (1990), and Turtle, Buse, and Korkie (1994). These terms are estimated by assuming constant correlations (ρ_{ij}), which substantially reduces the number of GARCH parameters to be estimated. Schwert and Seguin showed that the conditional covariances obtained using this approach provide a good description for monthly stock data.

We estimate the system of equations above using two approaches: (1) a bivariate GARCH framework; and, (2) a multivariate GARCH framework. For the bivariate specification, H_t is estimated with reference to past-error terms and variances for the security (or portfolio) under examination, along with the market portfolio. The multivariate estimation of H_t takes into account the past interrelationships among the covariances and error terms across all securities (or portfolios) and the market portfolio, in an attempt to capture important cross-sectional information. Hence, the multivariate system uses six portfolios in total.

As a practical matter, we follow the general portfolio formation approach of Conrad, Kaul, and Nimalendran (1991) and Karolyi and Kho (1996). Individual stocks are allocated to five size-sorted portfolios based on total market capitalization, and parameter estimates are obtained for these portfolios using the GARCH framework outlined in this section. We then obtain estimates of the time-varying expected portfolio returns implied by the model and determine expected returns for each of the individual stocks (R_{ipt}) within a given portfolio using the following regression:

$$R_{ipt} = \alpha_{ip} + \beta_{ip}E_{pt} + \eta_{ipt}, \quad (5)$$

where, E_{pt} is the expected return on the portfolio to which security i belongs, and η_{ipt} is the disturbance term. In this context, Conrad et al. (1991) pointed out that β_{ip} will measure the average covariance of security i's expected return with those of the other securities within the portfolio, thus providing a reasonable proxy for the estimated expected return of that security.[7]

Results

Simple OLS regressions on the nonlagged information variables (not reported here) and our univariate GARCH estimates indicate that the DY (positive coefficients) and DEFAULT (negative coefficients) instruments offer significant predictive power for excess portfolio returns, while the remaining variables are generally insignificant. These results are in agreement with Karolyi and Kho's (1996) observations using U.S. data. The average parameter estimates obtained from Equation 5 are reported in Table 3 along with the adjusted R^2 values. The results are similar using both estimation procedures. All 10 estimated β_{ip}s are signif-

Table 3
Parameter Estimates for the Market Model

The parameters of the market model are estimated with stock returns for each of five equally weighted size portfolios. The size-based portfolios are formed by ranking all 238 stocks in terms of market capitalization. Q1 represents a portfolio the smallest quintile of stocks, while Q5 represents the largest quintile. One-month Government of Canada treasury bill yields are used as a proxy for the riskfree rate and the TSE 300 is our market portfolio.

Market model

$$R_{p,t} - r_{f,t} = \gamma_{0,p} + \frac{h_{pMkt,t}}{h_{Mkt,t}}(\gamma'_{Mkt}Z_{t-1}) + \epsilon_{pt}$$

$$R_{Mkt,t} - r_{f,t} = \gamma'_{Mkt}Z_{t-1} + \epsilon_{Mkt,t}$$

The vector of instruments, $Z(t\text{-}1)$ consists of a constant, the 1-month T-bill yield, the term spread between 10-year and 1-month yields, the default spread between government and corporate debt, the lagged TSE 300 dividend yield, the conditional variance of the market excess returns and a January dummy. The conditional variances are estimated using a GARCH(1,1) framework. Returns for individual stocks are subsequently regressed on the expected portfolio returns generated by the market model.

$$R_{ipt} = \alpha_{ip} + \beta_{ip}E_{pt} + \eta_{ipt}$$

The alpha and beta values given below are averages across the stocks in each size category and average t-statistics are in parentheses.

	Market model					
	Bivariate GARCH			Multivariate GARCH		
Quintile	α	β	R^2 (%)	α	β	R^2 (%)
Q1	-0.0080	1.4203	2.68	-0.0047	1.2467	2.46
(small)	(-1.51)	(2.29)		(-0.99)	(2.21)	
Q2	-0.0005	1.3492	4.76	0.0009	1.2544	3.78
	(-0.11)	(2.95)		(0.21)	(2.66)	
Q3	-0.0047	1.7639	4.00	-0.0013	1.3553	4.55
	(-0.95)	(2.72)		(-0.30)	(2.89)	
Q4	0.0010	1.5652	5.62	0.0027	1.3978	5.29
	(0.23)	(3.19)		(0.60)	(3.10)	
Q5	0.0008	1.1539	1.75	0.0029	1.0263	2.78
(large)	(0.17)	(1.93)		(0.68)	(2.33)	

icant at the 5% level, while none of the alphas are significant.

Simulation results are generated using our time-varying risk (TVR) model and following the bootstrap methodology outlined in the previous section to produce 500 simulated return series. The difference between this and our random walk simulations is that the residuals are now estimated using Equation 5, before being scrambled and drawn with replacement. We note here that the entire series of residuals for all securities at one point in time is kept together and this vector is scrambled, which preserves the time dependencies in the individual error terms. Once again our trading strategy is implemented and portfolio returns calculated for each simulation. The results are presented in Table 4, and the empirical p-values may again be interpreted as outlined in the previous section.

The results are very similar using the bivariate or multivariate estimation procedures, and we observe a marked improvement in accounting for the observed pat-

Table 4
Bootstrap Tests for Market Models

The residual series for each stock is sampled with replacement using the parameter estimates from our market model (see Table 3) to generate simulated returns series. The momentum strategy is applied to each set of new returns. The mean returns for the simulated portfolios are averaged across 500 simulations. Note that P1 denotes the lowest past-return stocks and P10 denotes the highest past-return stocks. The empirical p-value denotes the proportion of the time the simulated mean return is larger than the actual mean return for a given portfolio.

		Simulations			
		Bivariate GARCH		Multivariate GARCH	
	Actual return (%)	Return (%)	Empirical p-value	Return (%)	Empirical p-value
P1	1.77	1.52	0.468	1.65	0.494
P2	2.69	2.72	0.516	2.82	0.534
P3	2.50	3.07	0.678	3.16	0.668
P4	3.30	3.34	0.532	3.34	0.510
P5	4.16	3.52	0.320	3.54	0.318
P6	4.35	3.72	0.314	3.71	0.326
P7	4.43	3.82	0.320	3.86	0.330
P8	3.42	4.01	0.680	4.03	0.664
P9	3.03	4.10	0.772	4.19	0.784
P10	5.87	4.21	0.148	4.26	0.138
P10-P1	4.10	2.69	0.188	2.61	0.168

tern in actual returns over the results for the random walk simulations. The empirical p-values for the bad portfolios decrease substantially from those presented in Table 2. In fact they are very close to 0.50 for portfolios P1 and P2 (the two biggest losers). Our models do not work as well for the P10 portfolio, where we observe a drop in the average empirical p-value from 0.194 to 0.143. However, if we examine the overall performance of the momentum strategy, as measured by the profitability of our P10-P1 portfolio, we observe that the simulated return series predicted by the TVR models offer a marked improvement in explaining these profits. The average empirical p-values for P10-P1 associated with the TVR models are roughly twice as large as those for the random walk model (0.178 vs. 0.096). For example, the 0.1880 p-value for P10-P1 using the bivariate GARCH specification indicates 94 out of 500 returns simulated using this model as the underlying equilibrium model exceeded the actual return of 4.10% per quarter. Hence, we may view a portion of the observed abnormal returns as appropriate compensation for risk that varies through time.

Transactions Costs and Momentum Trading

The long-term persistence of momentum in stock returns suggests that it may not be exploitable by investors. An obvious barrier to earning excess profits using any active trading strategy is the existence of transactions costs. For this purpose, we draw upon the work of Bhardwaj and Brooks (1992) to estimate the transactions costs (including commission fees and bid-ask spread effects) faced by investors. The performance of our trading strategy is then adjusted to reflect these transactions costs. Since investors operate in a variety of trading environments, we also perform a sensitivity analysis to examine the impact of different levels of transactions costs.

Bhardwaj and Brooks (1992) argued that "the January effect is primarily a low share price effect" (p. 553) due to higher transactions costs associated with the purchase and sale of lower priced common shares. This demonstrates the importance of accounting for individual price levels when determining the transactions costs of implementing an active trading strategy. Bhardwaj and Brooks' estimates of total transactions costs were based on a sample of 100 randomly selected NYSE

Table 5

Returns of Relative Strength Portfolios Net of Commission Fees and Bid-Ask Spreads (January 1979 - December 1990)

The relative strength portfolios are formed based on the past four quarterly returns (with double weight being given to the most recent quarterly return). The stocks are ranked in ascending order and ten equally weighted portfolios are formed. P1 represents the stocks with the weakest past performance, while P10 represents those stocks with the strongest past performance. P10-P1 refers to an investment strategy in which the stocks in the lowest ranking portfolio are sold short and the stocks in the highest ranking portfolio are purchased. Once the portfolios are formed the average return for each portfolio in each time period is adjusted to take into account both commission fees and bid-ask spreads. Setup costs and the costs of rebalancing the portfolios each time period are taken into account. We use the one-way median transactions costs (TC) determined by Bhardwaj and Brooks (1992). If the price of the stock (S) is less than $5 then TC= 6.268%; if 5 < S < = 10 then TC = 2.611%; if 10 < S < = 15 then TC = 2.472%; if 15 < S < = 20 then TC = 1.708%; finally if S > 20 then TC = 1.048%.

Returns net of commission fees, and bid-ask spreads	Stocks split into 10 equal portfolios[a]												
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1[b]	TSE 300[c]	Risk-free
Mean return (%)	0.13	0.17	-0.15	0.59	1.46	1.73	1.80	0.91	0.59	3.69	0.27	3.27	2.78
Volatility (std) (%)	12.6	10.4	10.6	8.9	10.0	9.6	9.3	9.7	9.8	11.3	11.2	9.4	0.8
β	1.025	0.909	0.942	0.843	0.965	0.947	0.905	0.945	0.887	1.019	-0.024	1.000	0
Average size (millions)	353.7	320.8	342.5	292.9	275.5	286.0	288.3	293.3	282.0	273.0	-80.70	n/a	n/a
Sharpe ratio	-0.212	-0.251	-0.278	-0.246	-0.132	-0.111	-0.105	-0.193	-0.225	0.080	0.024	0.052	0
Treynor ratio	-0.026	-0.029	-0.031	-0.026	-0.014	-0.011	-0.011	-0.020	-0.025	0.009	-0.116	0.005	n/a
α	-0.032	-0.003	-0.034	-0.026	-0.018	-0.015	-0.014	-0.023	-0.026	0.004	0.003	0	0
Average share price ($)	23.65	25.32	26.50	24.48	25.97	25.17	26.74	26.91	25.81	29.24	26.45	n/a	n/a
Median share price ($)	19.50	19.94	19.13	20.00	20.50	20.63	20.25	20.13	20.63	20.00	19.82	n/a	n/a
% of stocks (S < = $5)	1.1	4.0	5.7	5.0	6.9	6.6	6.6	5.0	4.6	5.1	3.1	n/a	n/a
% of stocks ($5 < S < = $10)	10.5	10.7	12.0	12.1	11.8	12.0	8.6	13.0	11.6	11.2	10.9	n/a	n/a
% of stocks ($10 < S < = $15)	16.5	16.4	17.3	14.3	12.9	15.9	18.8	15.1	17.3	15.2	15.8	n/a	n/a
% of stocks ($15 < S < = $20)	24.8	19.2	19.2	19.5	17.6	14.0	15.5	16.3	15.6	18.7	21.6	n/a	n/a
% of stocks (S > $20)	47.1	49.8	45.9	49.1	50.8	51.5	50.4	50.7	50.9	49.9	48.6	n/a	n/a

[a]In any given quarter there are the same number of stocks in each of the 10 portfolios. However, due to missing data, the number of stocks in each portfolio may be different from one quarter to the next. For example, in the first portfolio formation quarter there are 20 stocks in each portfolio, while in the last quarter there are only 12 stocks in each portfolio.

[b]Since P10-P1 is a self financing portfolio, it provides only a risk premium (not a riskless return plus a risk premium). Therefore, we use total return and not excess return above the riskfree rate when calculating the Sharpe, Treynor and alpha performance measures for P10-P1.

[c]The TSE 300 return was adjusted for transactions costs assuming a 2% set-up cost in the first quarter.

stocks in each of five price categories over the 1982-1986 period. They estimated the commission fees for each of these price ranges by applying the commission rate schedule of a prominent discount broker to observed trading data. Bid-ask spread costs are determined using the midway point between the bid and ask prices of actual trading data. We use Bhardwaj and Brooks' median estimates for commission fees, bid-ask spread costs, and total transactions costs, which are: (a) share price (S) < $5: 3.704%, 2.564% and 6.268%; (b) $5 < S < $10:

1.274%, 1.337% and 2.611%; (c) $10 < S < $15: 0.913%, 1.459% and 2.472%; (d) $15 < S < $20: 0.695%, 1.013% and 1.708%; and (e) S > $20: 0.403%, 0.645% and 1.048%.

Portfolio performance, net of transactions costs, is presented in Table 5. We note that the proportion of stocks in each of the price categories is similar across all portfolios, with approximately half of all stocks in the over-$20 price category. This implies there is no systematic price effect arising in the formation of our momentum portfolios. Transactions costs have a greater impact on the quarterly returns of P10 (which fall from 5.87% to 3.69%) than for those of P1 (which fall from 1.77% to 0.13%). This is attributable to the higher turnover of 71% per quarter for P10 versus 57% per quarter for P1. Our P10-P1 portfolio faces transactions costs on simultaneous purchases and sales of securities every quarter. Hence, it is not surprising that transactions costs have a significant impact on the P10-P1 quarterly returns, which are reduced from 4.10% to 0.27%.

This reduced profitability is reflected in the three traditional measures of portfolio performance included in Table 5. P10 still outperforms the market index based on these measures; however, only by a small margin. In particular, the P10 Sharpe and Treynor ratios of 0.080 and 0.009 are only slightly above the market index values of 0.052 and 0.005. P10-P1 now underperforms the market based on its Sharpe ratio of 0.024, which is well below the market index value, while its Jensen's alpha of 0.003 is very close to zero. These results indicate that following the P10-P1 investment strategy would not have produced superior performance for an investor facing these levels of transactions costs.

We recognize that Bhardwaj and Brooks' (1992) estimates may not be applicable to all investors for a variety of reasons, and we offer them only as a base case for the purpose of examining the impact of transactions costs. A potential bias in these estimates is due to the fact that they are based on NYSE data, which may underestimate the bid-ask spreads on a smaller exchange such as the TSE 300. This argument is consistent with the results of Atkins and Dyl (1997) who estimated the 1975-1989 median bid-ask spread costs for NYSE stocks (across all price categories) of 1.03% versus 3.75% costs for NASDAQ trades over the 1983-1991 period. Another concern regarding our base estimates is that institutional investors likely face much lower commission and bid-ask spread costs, which is confirmed by recent studies. For example, Berkowitz, Logue, and Noser (1988) estimated total transactions costs of 0.23% per transaction for institutional investors trading on the NYSE, while Chan and Lakonishok (1997) estimated total round trip costs of 0.54% for NYSE trades and 0.99% for NASDAQ trades.

The foregoing suggests the importance of examining the sensitivity of our trading strategy to different levels of transactions costs, since median costs (even if they are accurate) will not be appropriate guidelines for large categories of investors. Table 6 presents the impact of transactions costs on the profitability of our trading strategy for various levels of transactions costs. We scale the entire transactions cost structure used in Table 5 by a scaling factor denoted as gamma, where gamma = 1 for the base case (i.e., the Bhardwaj and Brooks, 1992, estimates). For example, when gamma = 1.2, total transactions costs for shares above $20 would be the Bhardwaj and Brooks estimate for that price category (1.048%) * 1.2 = 1.258%. Table 6 demonstrates that momentum trading would not be an attractive strategy for investors facing higher levels of trading costs. Thus, it may not be exploitable by the typical retail investor.

An investor following the P10-P1 strategy, facing transactions costs only 10% below the Bhardwaj and Brooks estimates (i.e., gamma = 0.9), could have earned a quarterly return of 0.66%. At this level of transactions costs, the P10-P1 portfolio would have outperformed the market index according to both its Sharpe ratio and its Jensen's alpha. For gamma = 0.5, we observe a significant improvement in the performance of P10, which generates a 4.78% quarterly return, a Sharpe ratio more than three times that of the market index, and a Treynor ratio that is five times that of the market index. The improvement in performance is even more dramatic for P10-P1, which generates a quarterly return of 2.19%, a large positive alpha, and a Sharpe ratio that is almost four times that of the market index. This evidence supports the profitability of momentum trading for investors facing lower levels of transactions costs. The implication is that institutional investors, who face trading costs well below those implied by our scaling factor of 0.5, could profitably exploit this investment opportunity. In fact, if we use 0.25% transactions costs across all price categories, we obtain the following performance measures for P10 and P10-P1: (1) quarterly returns of 5.59% and 3.78%, (2) Sharpe ratios of 0.259 and 0.336, and (3) alphas of 0.024 and 0.038.[8]

Conclusion

An often cited corollary of Murphy's Law suggests that things cannot possibly get any worse. Recent evidence on Canadian stock returns suggests this is not necessarily the case. In fact, empirical evidence indicates that poor past performance in stock returns will likely be followed by poor performance in the immediate future. All investors need not despair, however, since evidence also suggests strong past performance in stock returns

Table 6
Sensitivity of Relative Strength Portfolio Returns to Transactions Costs

The relative strength portfolios are formed based on the past four quarterly returns (with double weight being given to the most recent quarterly return). The stocks are ranked in ascending order and 10 equally weighted portfolios are formed. P1 represents the stocks with the weakest past performance, while P10 represents those stocks with the strongest past performance. P10-P1 refers to an investment strategy in which the stocks in the lowest ranking portfolio are sold short and the stocks in the highest ranking portfolio are purchased. In the base case (gamma = 1.0) transactions costs are identical to those shown in Table 5. The mean return and performance measures of the relative strength portfolios are recalculated assuming different levels of transactions costs. The transaction cost structure was shifted up and down by a scaling factor, gamma, which ranged from 50% to 130%. The same scaling factor was also applied to the 2% setup costs assumed for the TSE 300.

Level of TC (γ)		Stocks split into 10 equal portfolios[a]											TSE 300	Risk-free
		P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1[b]		
TC across all stocks (%)														
	Mean return (%)	1.63	2.49	2.29	3.08	3.94	4.13	4.21	3.21	2.83	5.59	3.78	3.31	2.78
0.25	Sharpe ratio	-0.092	-0.029	-0.047	0.033	0.118	0.143	0.154	0.044	0.005	0.259	0.336	0.056	0.000
	Treynor ratio	-0.011	-0.003	-0.005	0.003	0.012	0.014	0.016	0.004	0.000	0.029	-2.543	0.005	n/a
	α	-0.017	-0.007	-0.01	-0.001	0.007	0.009	0.01	-0.000	-0.004	0.024	0.038	0.000	0.000
	Mean return(%)	0.95	1.43	1.17	1.95	2.81	3.04	3.12	2.16	1.81	4.78	2.19	3.29	2.78
0.5	Sharpe ratio	-0.147	-0.131	-0.153	-0.094	0.003	0.027	0.036	-0.064	-0.101	0.177	0.195	0.055	0.000
	Treynor ratio	-0.018	-0.015	-0.017	-0.01	0.000	0.003	0.004	-0.007	-0.011	0.020	-1.190	0.005	n/a
	α	-0.023	-0.018	-0.021	-0.013	-0.004	-0.002	-0.001	-0.011	-0.014	0.015	0.022	0.000	0.000
	Mean return (%)	0.62	0.90	0.64	1.40	2.27	2.51	2.59	1.66	1.32	4.34	1.42	3.28	2.78
0.7	Sharpe ratio	-0.173	-0.179	-0.203	-0.155	-0.051	-0.028	-0.021	-0.116	-0.151	0.138	0.127	0.054	0.000
	Treynor ratio	-0.021	-0.020	-0.023	-0.016	-0.005	-0.003	-0.002	-0.012	-0.017	0.015	-0.695	0.005	n/a
	α	-0.027	-0.023	-0.026	-0.018	-0.010	-0.007	-0.006	-0.016	-0.019	0.011	0.014	0.000	0.000
	Mean return (%)	0.29	0.42	0.11	0.86	1.73	1.99	2.06	1.16	0.83	3.91	0.66	3.28	2.78
0.9	Sharpe ratio	-0.199	-0.227	-0.253	-0.215	-0.105	-0.084	-0.077	-0.168	-0.201	0.099	0.059	0.053	0.000
	Treynor ratio	-0.024	-0.026	-0.028	-0.023	-0.011	-0.008	-0.008	-0.017	-0.022	0.011	-0.291	0.005	n/a
	α	-0.030	-0.028	-0.031	-0.023	-0.015	-0.013	-0.012	-0.021	-0.024	0.006	0.007	0.000	0.000
	Mean return (%)	0.13	0.17	-0.15	0.59	1.46	1.73	1.80	0.91	0.59	3.69	0.27	3.27	2.78
1.0	Sharpe ratio	-0.212	-0.251	-0.278	-0.246	-0.132	-0.111	-0.105	-0.193	-0.225	0.080	0.024	0.052	0.000
	Treynor ratio	-0.026	-0.029	-0.031	-0.026	-0.014	-0.011	-0.011	-0.020	-0.025	0.009	-0.116	0.005	n/a
	α	-0.032	-0.003	-0.034	-0.026	-0.018	-0.015	-0.014	-0.023	-0.026	0.004	0.003	0.000	0.000
	Mean return (%)	-0.04	-0.08	-0.42	0.32	1.19	1.46	1.54	0.66	0.34	3.47	-0.11	3.27	2.78
1.1	Sharpe ratio	-0.225	-0.275	-0.303	-0.276	-0.159	-0.138	-0.133	-0.219	-0.249	0.061	-0.010	0.052	0.000
	Treynor ratio	-0.028	-0.032	-0.034	-0.029	-0.017	-0.014	-0.014	-0.023	-0.028	0.007	0.045	0.005	n/a
	α	-0.033	-0.033	-0.037	-0.029	-0.021	-0.018	-0.017	-0.026	-0.029	0.002	-0.001	0.000	0.000
	Mean return (%)	-0.37	-0.59	-0.95	-0.22	0.65	0.94	1.01	0.16	-0.15	3.04	-0.88	3.26	2.78
1.3	Sharpe ratio	-0.251	-0.323	-0.353	-0.336	-0.212	-0.192	-0.189	-0.270	-0.298	0.022	-0.079	0.051	0.000
	Treynor ratio	-0.031	-0.037	-0.040	-0.036	-0.022	-0.020	-0.020	-0.028	-0.033	0.003	0.328	0.005	n/a
	α	-0.037	-0.038	-0.042	-0.034	-0.026	-0.023	-0.022	-0.031	-0.034	-0.003	-0.009	0.000	0.000

[a] In any given quarter there are the same number of stocks in each of the 10 portfolios. However, due to missing data, the number of stocks in each portfolio may be different from one quarter to the next. For example, in the first portfolio formation quarter there are 20 stocks in each portfolio, while in the last quarter there are only 12 stocks in each portfolio.

[b] Since P10-P1 is a self-financing portfolio, it provides only a risk premium (not a riskless return plus a risk premium). Therefore, we use total return and not excess return above the risk-free rate when calculating the Sharpe, Treynor and alpha performance measures for P10-P1.

will persist. The above implies a profitable strategy would be to buy the strong past performers and sell the poor past performers. We employ this strategy to generate abnormal returns over the 1978-1990 period using Canadian common stocks.

Our evidence suggests that a portion of this profitability represents appropriate compensation for risk and risk premiums that vary through time. We also examine the impact of transactions costs on the implementation of this strategy and find that it may not be exploitable by the average retail investor facing higher levels of transactions costs. However, sensitivity analysis indicates that momentum trading may have merit for more nimble traders facing lower transactions costs.

References

Atkins, A. B., & Dyl, E. (1997). Transactions costs and holding periods for common stocks. *Journal of Finance, 52*, 309-325.

Banz, R. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9*, 3-18.

Berkowitz, S., Logue, S., & Noser, E. (1988). The total costs of transactions on the NYSE. *Journal of Finance, 43*, 97-112.

Bhardwaj, R., & Brooks, L. (1992). The January anomaly: Effects of low share price, transactions costs, and bid-ask bias. *Journal of Finance, 47*, 553-575.

Bodurtha, J., & Mark, N. (1991). Testing the CAPM with time varying risks and returns. *Journal of Finance, 46*, 1485-1505.

Bollerslev, T., Engle, R., & Woolridge, J. (1988). A capital asset pricing model with time varying covariances. *Journal of Political Economy, 96*, 116-131.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance, 47*, 1731-1764.

Campbell, J. (1987). Stock returns and the term structure. *Journal of Financial Economics, 18*, 373- 400.

Chan, L. K. C., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. *Journal of Finance, 51*, 1681-1713.

Chan, L. K. C., & Lakonishok, J. (1997). Institutional equity trading costs: NYSE versus NASDAQ. *Journal of Finance, 52*, 713-735.

Conrad, J., Kaul, G., & Nimalendran, M. (1991). Components of short-horizon individual security returns. *Journal of Financial Economics, 29*, 365-384.

DeBondt, W., & Thaler, R. (1985). Does the stock market overreact? *Journal of Finance, 42*, 557- 581.

Fama, E., & French, K. (1988a). Permanent and temporary components of stock prices. *Journal of Political Economy, 96*, 246-273.

Fama, E., & French, K. (1988b). Dividend yields and expected stock returns. *Journal of Financial Economics, 22*, 3-26.

Fama, E., & French, K. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics, 25*, 23-49.

Fama, E., & French, K. (1992). The cross-section of expected stock returns. *Journal of Finance, 47*, 427-465.

Fama, E., & Schwert, W. (1977). Asset returns and inflation. *Journal of Financial Economics, 5*, 115-146.

Ferson, W. (1989). Changes in expected security returns, risk, and the level of interest rates. *Journal of Finance, 44*, 1191-1217.

Ferson, W., Kandel, S., & Stambaugh, R. (1987). Tests of asset pricing with time-varying expected risk premiums and market betas. *Journal of Finance, 42*, 201-220.

Foerster, S. (1996). Back to the future–again. *Canadian Investment Review 9* (2), 13-17.

Foerster, S., Prihar, A., & Schmitz, J. (1994/1995). Back to the future. *Canadian Investment Review 7* (4), 9-13.

Harvey, C. (1989). Time varying conditional covariances in tests of asset pricing models. *Journal of Financial Economics, 24*, 289-317.

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

Jorgensen, B. (1995, October 13). Avoiding shoals as the tide turns. *The Financial Post*, p. 13.

Kan, R., & Kirikos, G. (1996). Now you see them, then you don't. *Canadian Investment Review 9* (2), 9-18.

Karolyi, G. A., & Kho, B. C., (1996). *Time varying risk premia and the returns to buying winners and selling losers: Caveat emptor et venditor.* (Working paper). Ohio State University, Columbus.

Keim, D., & Stambaugh, R. (1986). Predicting returns in the stock and bond markets. *Journal of Financial Economics, 17*, 357-390.

Korkie, R., & Plas, J. (1995). *Back to reality: Another look at share price momentum strategies* (Working paper). University of Alberta, Edmonton.

Malkeil, B. (1981). *A random walk down Wall Street* (2nd ed.). New York, NY: Norton.

McCurdy, T., & Morgan, I. (1992). Evidence of risk premiums in foreign currency futures markets. *Review of Financial Studies, 5*, 65-83.

Ng, L. (1991). Tests of the CAPM with time-varying covariances: A multivariate GARCH approach. *Journal of Finance, 46*, 1507-1521.

Schwert, G. W., & Seguin, P. (1990). Heteroskedasticity in stock returns. *Journal of Finance, 45*, 1129-1155.

Shanken, J. (1990). Intertemporal asset pricing: An empirical investigation. *Journal of Econometrics, 45*, 99-120.

Turtle, H., Buse, A., & Korkie, B. (1994). Tests of conditional asset pricing with time-varying moments and risk prices. *Journal of Financial and Quantitative Analysis, 29*, 15-29.

Notes

1. This issue was addressed in detail by Kan and Kirikos (1996), who argued that Foerster et al.'s results

(1994/1995) were primarily attributable to survivorship bias. Kan and Kirikos replicated Foerster et al.'s study using sample selection criteria designed to eliminate survivorship bias. In particular, they considered the 100 largest stocks (based on market capitalization) at the beginning of each quarter of their 1976-1991 sample period. This adjustment significantly reduced (but did not eliminate) the abnormal returns associated with momentum trading. Foerster (1996) noted that part of the reduced profitability observed by Kan and Kirikos may be attributed to the fact that they examined a different sample period from that used by Foerster et al.

2. We recognize that this portfolio is not truly a zero-cost portfolio in imperfect capital markets, due to margin requirements that restrict the seller from using the short sale proceeds. However, our equilibrium model is based on the assumption of perfect capital markets in which P10-P1 would represent a self-financing investment strategy. In addition, we account for the impact of transactions costs on the performance of this portfolio in the final section.
3. These criteria all assume that both the level of risk and the risk premium do not change throughout the sample period.
4. Because the return for P10-P1 is positive and its systematic risk is approximately zero, alpha must be positive since it is determined using a capital asset pricing model (CAPM) setting that assumes the existence of perfect capital markets. The Treynor ratio is uninformative for P10-P1 due to the small negative beta that would be the denominator in this ratio.
5. The regression equation is: $(\mathrm{Re}turn_{P10} - \mathrm{Re}turn_{P1}) = \alpha + \beta \ln\left(\frac{size(P10)}{size(P1)}\right)$.
6. Treasury bill and bond data was obtained from the CANSIM database for the 1978-1990 period.
7. It would be impractical to estimate a full covariance matrix for all 238 firms because of the noise associated with individual stock returns and the large number of required parameter estimates.
8. The 0.25% represents the average institutional costs for NYSE trades using the estimates provided by Berkowitz et al. (1988) and Chan and Lakonishok (1997).

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