Cross-Sectional and Time-Series Tests of Return Predictability: What Is the Difference?

Amit Goyal
Swiss Finance Institute, University of Lausanne

Narasimhan Jegadeesh
Goizueta Business School, Emory University

We compare the performance of time-series (TS) and cross-sectional (CS) strategies based on past returns. While CS strategies are zero-net investment long/short strategies, TS strategies take on a time-varying net long investment in risky assets. For individual stocks, the difference between the performances of TS and CS strategies is largely due to this time-varying net long investment. With multiple international asset classes with heterogeneous return distributions, scaled CS strategies significantly outperform similarly scaled TS strategies. (*JEL* G10, G11, G12, G14)

Received December 7, 2016; editorial decision October 5, 2017 by Editor Andrew Karolyi. Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

Much of the literature that examines return predictability based on past returns uses cross-sectional (CS) tests. For example, Jegadeesh and Titman (1993) rank the cross-section of stocks each month based on their return over the past 6 months and form decile portfolios each month. De Bondt and Thaler (1985) and Jegadeesh (1990) sort stocks at selected points in time based on past returns and find evidence of returns reversals. Numerous other studies also use such CS tests to examine stock return predictability based on stock characteristics, such as size and book-to-market ratios. Almost all of these studies use the cross-sectional ranking for portfolio formation.

Recently, Moskowitz, Ooi, and Pedersen (2012, MOP henceforth) report that a time-series (TS) momentum strategy is significantly more profitable. The TS strategy takes a long or short position on an asset by only looking back at its

We thank Nick Baltas, Clifton Green, Antti Ilmanen, Joonki Noh, Jeffrey Pontiff, and Dexin Zhao; two anonymous referees; the Executive Editor; Andrew Karolyi; and seminar participants at Emory University, Leibniz University Hannover, Southern Methodist University, University of Miami, and University of South Florida for helpful comments. Supplementary data can be found on The Review of Financial Studies Web site. Send correspondence to Amit Goyal, University of Lausanne, Building Extranef 226, 1015 Lausanne, Switzerland; telephone: +41-21-692-3676. E-mail: amit.goyal@unil.ch.

doi:10.1093/rfs/hhx131 Advance Access publication November 16, 2017

own performance during the ranking period, and not based on its relative rank across a cross-section. Asness, Moskowitz, and Pedersen (2013) examine CS strategies using the same set of assets as MOP, but both papers argue that TS and CS strategies are distinct and separate phenomena. MOP further conclude that TS strategies fully explain and subsume CS strategies.

The strong performance of TS strategies potentially has a number of economic implications. For instance, MOP (2012) state that TS strategies capture a significant feature of asset price behavior that can help us understand several economic phenomena, including the profitability of CS strategies. In that spirit, MOP recommend that a factor based on TS strategies be included in multifactor asset pricing models and suggest that this factor, TSMOM, can help explain existing asset pricing phenomena, including CS momentum premiums. He and Li (2015) also echo this view. Koijen et al. (Forthcoming) follow this recommendation and use the TSMOM factor in their analysis of carry strategies.

Much of the return predictability literature focuses on individual stocks, but the recent TS literature uses a sample of asset classes such as stock indices, bond indices, currencies, and commodities. We first examine whether MOP's (2012) findings regarding TS strategies generalize to individual U.S. stocks.[1] We use an approach similar to that in MOP and take long and short positions in each stock based on its past excess returns over horizons ranging from 1 to 60 months. For example, when we use a 1-month ranking period, we take long positions in all stocks with positive excess returns over the previous month and short positions in other stocks. We evaluate the performance of this strategy and compare it with a CS strategy that takes long positions in stocks that have returns greater than the cross-sectional average return and short positions otherwise.

We find striking differences between the excess returns for the TS strategies and the corresponding CS strategies, similar to MOP's (2012) findings for asset classes. For example, a CS strategy that ranks stocks based on past 1-month returns and holds it for 1 month (we will refer to this strategy as the 1×1 strategy; more generally, the first number is the ranking period, and the second number is the holding period) earns an annualized return of -5.09% consistent with the evidence of short-horizon contrarian profits in Jegadeesh (1990). In contrast, the 1×1 TS strategy earns positive excess returns of 4.03%. Similarly, the 60×60 CS strategy earns significantly negative annualized returns of -2.08% consistent with long-horizon return reversals that De Bondt and Thaler (1985) document, but the 60×60 TS strategy earns significantly positive excess returns of 7.50%. For the 6×6 strategy, both CS and TS strategies earn significantly positive excess returns.

[1] Empirical regularities documented for indexes and asset classes need not carry over to individual stocks and vice versa because indexes diversify away firm-specific returns. The literature has historically examined whether several return anomalies documented with individual stocks carry over to asset classes. For example, see Chan, Hameed, and Tong (2000), Menkhoff et al. (2012), and Asness, Moskowitz, and Pedersen (2013).

To further evaluate the relative performance, we implement a set of the tests proposed by MOP (2012). Specifically, we regress CS excess returns against TS excess returns and vice versa, and test whether the alphas in these regressions are different from zero. We find that when we regress CS profits against TS profits, the alphas are significantly negative for short and long ranking periods. In contrast, the alphas are significantly positive when we regress TS profits against CS profits.

Overall, our results for individual U.S. stocks are consistent with those for aggregate international asset classes in MOP (2012). To derive additional economic insights from the performance of TS strategies, we need to understand the sources of differences in the performance of TS and CS strategies. As we discussed earlier, the difference between TS and CS strategies pertains to the threshold for taking long or short positions in an asset; zero excess returns in the case of TS and cross-sectional average returns in the case of CS. How does a simple change in threshold for portfolio formation result in a large return difference? Why does this change result in a distinctly different phenomenon, as Asness, Moskowitz, and Pedersen (2013) and MOP suggest? How does this threshold change cause the TS strategy to become a "central driver of cross-sectional momentum," as MOP conclude? We address all these questions.

One important difference is that CS strategies are, by construction, zero net-investment strategies but TS strategies are not. The CS strategies invest \$1 on the long side and \$1 on the short side, but TS strategies generally take long or short positions in the market depending on the number of stocks with positive and negative excess returns. Because more stocks earned positive returns than negative returns during the sample period, TS strategies take bigger long positions than short positions. For example, the average long and short positions for a 12×1 TS strategy are \$1.24 and \$0.76, respectively. Because of the positive net long position in risky assets, the positive intercept in the regression of TS excess returns against CS excess returns includes the risk component inherent in the TS strategy and, therefore, one cannot draw reliable inferences about relative performance using cross-alpha regressions with excess returns, like in MOP (2012).

To make these strategies directly comparable, we add to the CS strategy a time-varying investment in the market (TVM) equal to the dollar value of the difference between the long and short sides of the TS strategy each month. We label this strategy as CS_{TVM}. If the performances of TS and CS_{TVM} are the same or if CS_{TVM} performs better than TS, then it would be a stretch to view the TS strategy as a distinctly different phenomenon that potentially sheds new economic insights. After all, one could add a TVM to any anomaly and come up with numerous such phenomena. In contrast, if the TS strategy outperforms CS_{TVM}, then it would imply that TS strategies are, in fact, better at identifying assets that would outperform or underperform their benchmarks and TS strategies could potentially subsume CS strategies. The TS strategy could also then explain other phenomena besides CS strategies and shed new economic insights, as MOP (2012) claim.

Both TS and CS_{TVM} strategies perform similarly with individual stocks for the horizons over which Jegadeesh and Titman (1993) find momentum strategies are profitable. Therefore, the seemingly superior performance of TS strategies over CS strategies in cross-alpha tests is entirely due to TS strategies' net long positions. The 1×1 TS strategy is significantly different from the corresponding CS_{TVM} strategy because CS strategies exploit returns reversals that Jegadeesh (1990) documents, but the TS strategies miss this effect. Therefore, investors who seek to trade based on short-term return reversals would do better with the CS approach. Overall, TS strategies do not subsume CS strategies with individual stocks.

We also compare the performances of these two strategies for a sample of international asset classes that MOP (2012) examine: equity and bond indexes, commodities, and currencies. MOP's TS strategies for asset classes assign portfolio weights equal to 40% divided by the asset class volatility, so that for each asset class the ex-ante annualized volatility (is) 40%. MOP's scaling magnifies the size of the long and short positions, as well as the net long positions and the magnitude of the profits. Therefore, our tests compare MOP's scaled TS strategies with similarly scaled CS and CS_{TVM} strategies.

Unlike with individual stocks, we find significant differences between scaled CS and TS strategies with multiple asset classes with heterogeneous return distributions. With international asset classes, scaled TS strategies significantly underperform scaled CS strategies. This underperformance is partly because of differences in asset class compositions of the portfolios selected by TS and CS strategies. The long sides of the TS strategies on average take on bigger positions in bonds than the short side because bonds have positive excess returns more often than other asset classes. This disparity is magnified in the scaled TS strategies because bonds have the lowest volatility among all asset classes. For instance, the 12×1 scaled TS strategy is \$2.22 long and \$0.97 short in bonds on average. Bonds have the smallest excess returns among all asset classes in the sample and therefore these large net long positions hurt the performance of TS strategies. Additionally, CS strategies exhibit a better ability to identify overvalued and undervalued bonds.

Contrary to our conclusions, MOP (2012) claim that TS strategies subsume CS strategies and that "time-series momentum is a central driver of cross-sectional momentum." MOP's claims are based on a comparison of the relative performance of their scaled TS factor with an unscaled CS momentum factor, which they refer to as TSMOM and XSMOM respectively. XSMOM is \$1 long for every \$1 short, but TSMOM is on average \$3.28 long and \$1.73 short.[2] Therefore, TSMOM is a factor with a positive net long position but

[2] The magnitude of the long and short positions for the TSMOM factor is from our sample. MOP (2012) do not report the magnitude of the long and short sides for their strategies.

XSMOM is a zero net-investment strategy. Moreover, the sum of the long and short sides of TSMOM, which is its total active position in risky assets, is \$5 but the total active position of XSMOM is only \$2.[3] Scaling up active positions of strategies that earn positive returns scales up their returns as well. For instance, a CS factor with \$2.5 long and \$2.5 short will earn two-and-a-half times the excess returns of XSMOM. Our tests account for these differences by scaling CS strategies.

We find that TS and CS_{TVM} strategies perform similarly when we implement them within three of the individual asset classes, viz. equities, currencies, and commodities. Any difference between TS and CS strategies within these asset classes are due to the net long positions taken by TS strategies. For bonds, CS_{TVM} outperforms TS strategies, indicating that the cross-sectional approach is better at identifying over and undervalued bonds than the TS approach.

Our analysis of the sources of differences between TS and CS strategies clears up some confusion in the literature and adds new economic insights. For instance, MOP (2012) propose that asset pricing models use a TSMOM factor, which could "explain existing asset pricing phenomena, such as cross-sectional momentum premiums." Our results show that for individual stocks, TSMOM factor is really a combination of the CS momentum factor used in the Carhart (1997) model plus a time-varying investment in the market. The component related to time-varying investment in the market of the TS momentum factor is redundant in usual asset pricing models. The performance of the remaining component (related to a zero net-cost time-series strategy) is similar to that of a CS factor for individual stocks. Therefore, it is unlikely that TSMOM will be an incrementally useful factor for individual stocks. The case for a TSMOM factor for international asset classes is even weaker since the TSMOM factor significantly underperforms a similarly scaled cross-sectional factor.

MOP (2012) also use Lo and MacKinlay (1990), henceforth LM)-type strategies to compare TS and CS approaches. Specifically, MOP apply the LM methodology to examine "what features are common and unique to the two strategies." The LM-type strategies do not correspond to the scaled or unscaled strategies in MOP. In fact, we show that the LM-type TS strategy that MOP use is mathematically identical to the LM-type CS strategy plus a time-varying investment in the equal-weighted index of all assets in the sample. Therefore, the differences between the LM-type TS and CS strategies are entirely due to the time-series behavior of equal-weighted index returns, and they do not shed any light on the sources of differences between the TS and CS strategies that MOP use in much of their empirical tests.

---

[3] Futures contracts do not require any upfront cash payment, and margins for future contracts can be posted in interest-bearing assets. However, futures positions expose investors to the risk of the underlying assets, and, hence, futures positions are active positions.

1. Profitability of Past Return-Based Strategies: U.S. stocks

Our sample of common stocks comprises stocks with share codes 10 or 11 in the CRSP database during the 1946 to 2013 period. The share code criterion filters out American depository receipts, units, American trust components, closed-end funds, preferred stocks, and real estate investment trusts. Our sample also excludes micro-cap stocks to avoid potential biases in computed returns, which are particularly severe for low priced stocks (see Blume and Stambaugh 1983 and Lyon, Barber, and Tsai 1999). We, therefore, follow the literature (e.g. Jegadeesh and Titman 1993) and exclude micro-cap stocks. A micro-cap stock is defined as a stock below the 20th percentile of NYSE market capitalization at the end of the ranking period.

We examine the performances of a CS and a TS strategy similar to the one in MOP (2012). Specifically, we sort stocks based on prior returns during a ranking period ranging from 1 to 60 months. Portfolios holding periods range from 1 to 60 months. We use overlapping portfolios for holding periods greater than 1 month, like in Jegadeesh and Titman (1993).

For the CS strategy, at each ranking date, we sort stocks into two equal-weighted portfolios based on their prior raw returns in excess of the cross-sectional average. We go long (short) in stocks with returns higher (lower) than the cross-sectional average. The return to a CS strategy in month t is given by

$$R_t^{CS} = \frac{1}{N^+} \sum\nolimits_{R_{it-1} \geqslant \bar{R}_{t-1}} R_{it} - \frac{1}{N^-} \sum\nolimits_{R_{it-1} < \bar{R}_{t-1}} R_{it}, \qquad (1)$$

where R_{it-1} is the ranking period excess return on the i^{th} stock, $\bar{R}_{t-1}$ is the cross-sectional equal-weighted average of the ranking period returns, and $N^+(N^-)$ is the number of stocks with returns higher (lower) than the cross-sectional average. By construction, the CS strategy invests \$1 each month on both the long and short sides.

For the TS strategy, we sort stocks based on their prior raw returns in excess of the risk-free rate. We go long (short) in stocks with excess returns bigger (smaller) than zero. Following MOP (2012), the return to TS strategy is given by[4]

$$R_t^{TS} = \frac{2}{N} \left(\sum\nolimits_{R_{it-1} \geqslant 0} R_{it} - \sum\nolimits_{R_{it-1} < 0} R_{it} \right), \qquad (2)$$

where N is the total number of stocks. The factor of two in the numerator of Equation (2) ensures that the total long plus short positions, or the total active position, of TS strategies is \$2, which equals that for CS strategies. For instance, if the number of stocks with positive and negative ranking period excess returns

[4] MOP (2012) use international asset classes and scale up the weights for each asset class so that the scaled volatility matched that of average individual stocks. Since we are dealing with individual stocks in this section, we use equal weights.

Table 1
Portfolio returns to prior return sorts based on time-series and cross-sectional strategies

	Holding period					
Ranking period	1	3	6	12	36	60
A. Time-series strategy						
1	4.03	2.22	2.29	2.48	0.88	0.94
	(1.90)	(1.60)	(2.15)	(3.15)	(2.06)	(2.90)
3	6.12	4.65	4.35	4.28	2.02	2.25
	(2.68)	(2.31)	(2.59)	(3.27)	(2.66)	(3.51)
6	7.97	6.35	5.79	4.96	2.38	2.81
	(3.26)	(2.75)	(2.68)	(2.83)	(2.27)	(3.17)
12	9.25	7.36	6.20	3.45	2.58	3.29
	(3.59)	(2.94)	(2.61)	(1.68)	(1.92)	(2.82)
36	5.54	5.29	4.56	3.98	5.44	5.71
	(2.32)	(2.24)	(1.97)	(1.82)	(2.76)	(3.13)
60	6.42	6.31	6.17	5.90	7.04	7.71
	(2.68)	(2.62)	(2.57)	(2.51)	(3.14)	(3.61)
B. Cross-sectional strategy						
1	−5.09	−1.24	0.20	1.10	0.03	−0.05
	(−5.03)	(−1.67)	(0.36)	(2.65)	(0.14)	(−0.36)
3	−0.77	1.12	2.06	2.43	0.24	0.04
	(−0.62)	(1.07)	(2.33)	(3.66)	(0.69)	(0.18)
6	2.33	3.48	3.90	3.02	0.15	−0.04
	(1.75)	(2.79)	(3.48)	(3.45)	(0.33)	(−0.13)
12	4.98	4.93	3.86	1.72	−0.45	−0.55
	(3.56)	(3.71)	(3.13)	(1.63)	(−0.76)	(−1.19)
36	−0.08	0.24	−0.09	−0.80	−1.44	−1.62
	(−0.07)	(0.21)	(−0.09)	(−0.82)	(−2.01)	(−2.75)
60	−0.61	−0.39	−0.53	−1.30	−1.97	−2.00
	(−0.61)	(−0.40)	(−0.57)	(−1.49)	(−2.89)	(−3.40)

We sort stocks based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy is the equal-weighted portfolio of all stocks with positive excess returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. The long portfolio under the CS strategy is the equal-weighted portfolio of all stocks with returns in excess of cross-sectional mean returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. We use overlapping portfolios, like in Jegadeesh and Titman (1993), for holding periods greater than 1 month. This table reports the annualized excess returns of long minus short portfolios. Numbers in parentheses are the corresponding t-statistics. We use only non-micro-cap stocks at the time of sorting. A stock is defined as non-micro-cap if it is above the 20th percentile of NYSE market capitalization. The sample period is from 1946 to 2013.

were equal, the factor two would ensure that the TS strategy invests $1 each month on the long and short sides.

The CS strategies that we examine are conceptually similar to those in the literature. However, our strategies form only two portfolios with the entire sample of stocks, while the literature typically examines the profitability of stocks with extreme returns during the ranking period. We choose the two-portfolio strategy, so that the results are more directly comparable with those with the TS strategy than those with the ones in the literature.

Panel A of Table 1 presents the excess returns for various TS strategies that vary by ranking period and by holding period from 1 to 60 months. All strategies earn positive excess returns that tend to increase with the ranking period. For example, the annualized excess returns for a 1-month ranking period and a

1-month holding period strategy (the 1×1 strategy) is 4.03%, compared with 9.25% for the 6×1 strategy and 6.42% for the 60×1 strategy.

Panel B of Table 1 presents the excess returns for the CS strategies. The 1×1 CS strategy earns -5.09%, which is reliably less than zero. Our result is consistent with the evidence of short-horizon contrarian profits in Jegadeesh (1990). In contrast, the 1×1 TS strategy in panel A earns positive excess returns of 4.03%. Similarly, the 60×60 CS strategy earns significantly negative returns of -2.00%, consistent with long-horizon return reversals that De Bondt and Thaler (1985) document. In contrast, the 60×60 TS strategy earns significantly positive excess returns of 7.71%. Both CS and TS 6×6 strategies earn significantly positive excess returns, which is consistent with the momentum evidence in Jegadeesh and Titman (1993).

1.1 Cross-alpha comparison

MOP (2012) present the following comparison of TS and CS profits to assess their relative importance. They regress CS profits against TS profits and find that the intercept is insignificant, but when they regress TS profits against CS profits, the intercept is significantly positive. Therefore, they conclude that TS momentum explains CS momentum, but TS momentum is not fully captured by CS momentum. We conduct a similar test with our TS and CS profits.

Table 2 reports the alphas from regression of excess returns for the TS strategies against the excess returns for CS strategies and vice versa. We report results for holding periods equal to ranking period, as well as for a holding period of 1 month. When TS excess returns are the dependent variables, the intercepts are always positive and significant at short and long horizons. For example, the alphas for the 1×1 and 60×60 strategies are 10.78% and 10.86%. When we regress CS excess returns against TS excess returns, the alphas are significantly negative at short and long horizons. For example, the alphas for 1×1 and 60×60 strategies are -6.31% and -2.93%, respectively. The alpha for the 6×6 strategy is 1.79%, which is the only significantly positive alpha.

The significantly positive intercepts, when TS excess returns are dependent variables, are similar to what MOP (2012) find. The intercepts, when CS profits are the dependent variables, are also significant in seven out of 12 regressions. The significant alphas with TS strategies are larger in magnitude than the ones with the CS strategies.

The primary difference between these strategies is that the TS strategy uses contemporaneous risk-free rate as the reference point for deciding on the long and short sides, but the CS strategy uses equal-weighted index returns. Why does this difference in reference point result in excess returns of opposite signs for TS and CS strategies at both the longest and shortest ranking and holding periods? Which of these strategies are more consistent with behavioral models for individual stocks? We need to understand the sources of these differences to answer such questions.

Table 2
Cross-alphas of portfolio returns based on time-series and cross-sectional strategies

	Holding period = Ranking period		Holding period = 1 month	
Explanatory variable→	CS	TS	CS	TS
Dependent variable→	TS	CS	TS	CS
Ranking period				
1	10.78	−6.31	10.78	−6.31
	(6.46)	(−8.03)	(6.46)	(−8.03)
3	3.18	−0.55	7.06	−2.95
	(2.17)	(−0.71)	(4.12)	(−3.18)
6	0.52	1.79	4.98	−0.69
	(0.33)	(2.23)	(2.83)	(−0.72)
12	1.29	0.58	2.89	1.51
	(0.82)	(0.71)	(1.54)	(1.48)
36	7.54	−2.49	5.64	−1.78
	(4.51)	(−4.09)	(3.02)	(−1.93)
60	10.86	−2.93	7.21	−2.03
	(5.61)	(−5.47)	(3.56)	(−2.41)

We sort stocks based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy is the equal-weighted portfolio of all stocks with positive excess returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. The long portfolio under the CS strategy is the equal-weighted portfolio of all stocks with returns in excess of cross-sectional mean returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. We use overlapping portfolios, like in Jegadeesh and Titman (1993), for holding periods greater than 1 month. This table reports the intercepts from time-series regressions of the annualized excess returns of CS strategies against TS strategies and vice versa. Numbers in parentheses are the corresponding t-statistics. We report statistics for strategies with holding period equal to ranking period (corresponding to diagonal entries in Table 1) and for strategies with the holding period equal to 1 month (corresponding to entries in the first column in Table 1). We use only non-micro-cap stocks at the time of sorting. A stock is defined as non-micro-cap if it is above the 20th percentile of NYSE market capitalization. The sample period is from 1946 to 2013.

2. Sources of the Difference between TS and CS Strategy Profits

CS strategies by construction are zero-dollar investment strategies. In contrast, TS strategies in general take long or short positions in the market depending on the relative number of stocks with positive and negative excess returns. If more than half the assets have positive past excess returns in any given month, the portfolio for that month would have a net long position in risky assets and net short position otherwise.[5] If the average premium earned by risky assets is positive over the sample period, then the TS strategy takes an average net long active position. In contrast, the CS strategy takes a zero net active position because it invests equal amounts in long and short positions each period.

The net long position is not deliberately built into TS strategies but follows mechanically from the way these strategies are constructed. When we compare TS and CS strategies, we should account for the additional risk premium that TS strategies earn relative to CS strategies because of this net long position. To put these strategies on a common footing, we can follow a mechanical

[5] Because we consider excess returns in our portfolio strategies, we implicitly borrow any investment in the risky assets at the risk-free rate, and we invest all proceeds from short positions in the risk-free asset. Therefore, each leg of the strategy is a net zero-dollar position. However, the net position in the risky assets is in general nonzero for the TS strategy because the number of long stocks and short stocks are not equal. We will refer to net nonzero positions in risky assets as “net long” positions.

investment rule that invests the net long position in a random stock and add it to CS strategies. Since the expected return on a random stock equals the expected return on the equal-weighted index, we invest the net long amount in the equal-weighted market index. If one is concerned about trading costs, one could instead invest in a liquid ETF or stock index futures most highly correlated with the equal-weighted index because the expected abnormal returns on all these passive investments equal zero.

The dollar amount that we invest in the market to match net long positions varies through time. For instance, if there are 60 (40) stocks with positive (negative) ranking-period excess returns in a particular month, then the TS strategy invests \$1.2 long and \$0.8 short. The net long position of \$0.4 is invested in the equal-weighted index. If the numbers of stocks with positive and negative excess returns are reversed, then the net long position is −\$0.4 and we take a short position of \$0.4 in the equal-weighted index in that month. We refer to this time-varying investment in the market as TVM and label the sum of CS and TVM strategy as CS_{TVM}.

If the performance of TS strategy is the same as that of CS_{TVM} strategy, then one would conclude that the TS strategy is not a distinctly different phenomenon that sheds new economic insights. In contrast, if the TS strategy outperforms the CS_{TVM} strategy, then one can infer that TS strategies are better at identifying assets that would outperform or underperform the benchmarks in the future.

We compare the performance of TS, CS, and CS_{TVM} strategies in Table 3. This table also presents returns to TS−CS and TS−CS_{TVM} strategies. We present results for holding periods equal to ranking period, as well as for the holding period of 1 month. The last two columns in each panel show the average dollar long and short positions for the TS strategies. The net long for the 1×1 strategy is \$0.12 (on average \$1.06 was invested on the long side and \$0.94 was invested on the short side in this strategy). Because more stocks on average earned positive than negative monthly excess returns during the sample period, the average net long position is positive. The net long position monotonically increases with the ranking period, from \$0.12 for the 1×1 strategy to \$0.99 for the 60×60 strategy. Since the overall market's excess return was positive during the sample period, the TS strategy takes on a relatively bigger net long position as the ranking period length increases. Figure 1 presents the net long positions for the 1×1, 6×6, 12×12, and 60×60 strategies. The net long positions become less volatile as the ranking period increases as a higher fraction of stocks has positive long-horizon returns than short-horizon returns. In fact, the net long position is rarely negative for the 60×60 strategy.

The difference between TS and CS excess returns exhibit a U-shaped pattern, with the largest difference at the long and short ends. The differences are 9.12% and 9.71% for the 1×1 and 60×60 strategies, respectively, which are both statistically significant. The differences for the 6×6 and 12×12 strategies are 1.89% and 1.73%, respectively, both of which are statistically insignificant. There is a similar, though less pronounced, U-shaped pattern for the holding

Table 3
Comparison of time-series and cross-sectional strategies

	Holding period = Ranking period							Holding period = 1 month						
Ranking period	TS	CS	CS_{TVM}	TS−CS	TS−CS_{TVM}	$Long	$Short	TS	CS	CS_{TVM}	TS−CS	TS−CS_{TVM}	$Long	$Short
1	4.03	−5.09	2.85	9.12	1.18	1.06	−0.94	4.03	−5.09	2.85	9.12	1.18	1.06	−0.94
	(1.90)	(−5.03)	(1.17)	(5.45)	(2.57)	(4.15)	(4.15)	(1.90)	(−5.03)	(1.17)	(5.45)	(2.57)	(4.15)	(4.15)
3	4.65	1.12	4.25	3.52	0.40	1.14	−0.86	6.12	−0.77	4.96	6.89	1.16	1.14	−0.86
	(2.31)	(1.07)	(1.81)	(2.35)	(0.89)	(9.95)	(9.95)	(2.68)	(−0.62)	(1.85)	(3.97)	(2.18)	(8.54)	(8.54)
6	5.79	3.90	5.75	1.89	0.03	1.18	−0.82	7.97	2.33	7.28	5.64	0.69	1.18	−0.82
	(2.68)	(3.48)	(2.25)	(1.19)	(0.07)	(13.17)	(13.17)	(3.26)	(1.75)	(2.50)	(3.15)	(1.15)	(11.10)	(11.10)
12	3.45	1.72	2.88	1.73	0.57	1.24	−0.76	9.25	4.98	9.42	4.27	−0.17	1.24	−0.76
	(1.68)	(1.63)	(1.18)	(1.08)	(1.09)	(18.59)	(18.59)	(3.59)	(3.56)	(3.09)	(2.25)	(−0.27)	(15.13)	(15.13)
36	5.44	−1.44	4.93	6.88	0.51	1.40	−0.60	5.54	−0.08	5.12	5.62	0.42	1.39	−0.61
	(2.76)	(−2.01)	(2.13)	(4.05)	(0.97)	(36.71)	(36.71)	(2.32)	(−0.07)	(1.80)	(2.97)	(0.63)	(28.46)	(28.46)
60	7.71	−2.00	7.20	9.71	0.51	1.50	−0.50	6.42	−0.61	6.83	7.03	−0.41	1.48	−0.52
	(3.61)	(−3.40)	(2.90)	(4.98)	(0.94)	(47.93)	(47.93)	(2.68)	(−0.61)	(2.42)	(3.43)	(−0.60)	(37.54)	(37.54)

We sort stocks based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy is the equal-weighted portfolio of all stocks with positive excess returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. The long portfolio under the CS strategy is the equal-weighted portfolio of all stocks with returns in excess of cross-sectional mean returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. We use overlapping portfolios, like in Jegadeesh and Titman (1993), for holding periods greater than 1 month. This table reports long minus short excess returns for TS and CS strategies. The CS_{TVM} strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (please refer to text for details). $Long and $Short are the average dollar positions of the TS strategy. Numbers in parentheses are the corresponding t-statistics (t-statistics for $Long and $Short are calculated for the null of $1 and −$1, respectively). This table reports statistics for strategies with holding period equal to ranking period (corresponding to diagonal entries in Table 1) and for strategies with the holding period equal to 1 month (corresponding to entries in the first column in Table 1). We use only non-micro-cap stocks at the time of sorting. A stock is defined as non-micro-cap if it is above the 20th percentile of NYSE market capitalization. The sample period is from 1946 to 2013.

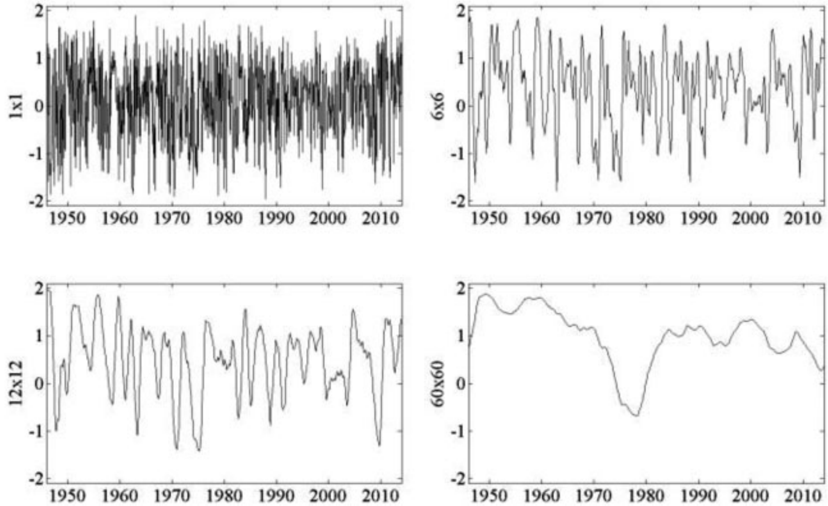

Figure 1
Net long positions for time-series strategies with individual stocks
The long portfolio under the time-series (TS) strategy is the equal-weighted portfolio of all stocks with positive excess returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. The figure shows the net long position each month (in dollars) for TS strategies with both ranking and holding periods equal to 1, 6, 12, and 60 months. We use only non-micro-cap stocks at the time of sorting. A stock is defined as non-micro-cap if it is above the 20th percentile of NYSE market capitalization. The sample period is from 1946 to 2013.

period of 1 month. For instance, differences are 9.12%, 4.27%, and 7.03% for the 1×1, 12×1, and 60×1 strategies, respectively, which are all statistically significant.

The differences between TS and CS_{TVM}, on the other hand, are small and mostly statistically insignificant. For instance, TS$-$$\text{CS}_{\text{TVM}}$ is only 1.18% and 0.51% for the 1×1 and 60×60 strategies, respectively. In fact, apart from the 1×1 and 3×1 strategies, none of these differences are statistically significant at the 95% level. Thus, an apples-to-apples comparison of TS and CS_{TVM} strategies reveals that these strategies perform about the same.

We also compare the performances of decile portfolios and zero net investment 10$-$1 (long winner decile and short loser decile) portfolios formed using TS and CS approaches. The returns on TS decile portfolios are generally the same as those of the corresponding CS portfolios, and the performances of the 10$-$1 portfolios are also mostly equal. We report these results in the Internet Appendix Table A1. Our findings here further show that TS and CS strategies perform similarly, after we account for the effects of TVM.

2.1 Risk-adjusted returns

Recall that CS is a zero net long strategy, whereas TS and CS_{TVM} have net long positions. This means that TS$-$CS is a net long strategy, while TS$-$$\text{CS}_{\text{TVM}}$ is a zero net long strategy. Presumably, the market factor should account for

Table 4
Alphas based on time-series and cross-sectional strategies

	Holding period = Ranking period					Holding period = 1 month				
Ranking period	TS	CS	CS_{TVM}	TS−CS	$TS-CS_{TVM}$	TS	CS	CS_{TVM}	TS−CS	$TS-CS_{TVM}$
A. CAPM alpha										
1	6.68	−4.14	5.73	10.82	0.95	6.68	−4.14	5.73	10.82	0.95
	(3.28)	(−4.16)	(2.43)	(6.61)	(2.06)	(3.28)	(−4.16)	(2.43)	(6.61)	(2.06)
3	5.15	1.70	4.74	3.45	0.40	7.26	0.17	6.26	7.09	0.99
	(2.54)	(1.61)	(2.00)	(2.28)	(0.90)	(3.17)	(0.14)	(2.33)	(4.05)	(1.85)
6	5.24	4.08	4.97	1.16	0.28	8.84	3.02	8.14	5.82	0.70
	(2.41)	(3.61)	(1.93)	(0.73)	(0.55)	(3.59)	(2.27)	(2.78)	(3.22)	(1.15)
12	1.40	1.20	0.11	0.21	1.29	8.65	5.16	8.48	3.49	0.17
	(0.70)	(1.13)	(0.05)	(0.13)	(2.59)	(3.33)	(3.65)	(2.76)	(1.83)	(0.26)
36	−0.12	−2.54	−1.83	2.42	1.72	2.23	−0.75	0.76	2.98	1.47
	(−0.08)	(−3.79)	(−1.13)	(1.85)	(3.90)	(0.98)	(−0.64)	(0.29)	(1.66)	(2.39)
60	0.86	−3.06	−0.95	3.93	1.81	1.32	−1.40	0.36	2.73	0.97
	(0.66)	(−5.74)	(−0.65)	(2.92)	(4.03)	(0.64)	(−1.43)	(0.15)	(1.54)	(1.59)
B. FF 3-factor alpha										
1	6.88	−3.72	6.08	10.60	0.79	6.88	−3.72	6.08	10.60	0.79
	(3.32)	(−3.69)	(2.54)	(6.37)	(1.70)	(3.32)	(−3.69)	(2.54)	(6.37)	(1.70)
3	4.75	2.23	4.53	2.52	0.23	6.89	0.71	6.12	6.18	0.77
	(2.31)	(2.10)	(1.89)	(1.65)	(0.51)	(2.97)	(0.57)	(2.25)	(3.49)	(1.44)
6	5.24	5.04	5.45	0.21	−0.21	8.83	3.94	8.60	4.89	0.23
	(2.37)	(4.50)	(2.09)	(0.13)	(−0.42)	(3.53)	(2.97)	(2.90)	(2.68)	(0.39)
12	3.01	3.53	2.63	−0.52	0.38	9.08	6.84	9.68	2.23	−0.60
	(1.49)	(3.73)	(1.12)	(−0.33)	(0.87)	(3.44)	(5.02)	(3.12)	(1.16)	(−0.99)
36	0.22	−0.45	−0.73	0.67	0.95	4.42	2.28	4.11	2.14	0.31
	(0.15)	(−0.86)	(−0.45)	(0.53)	(2.57)	(1.96)	(2.29)	(1.59)	(1.18)	(0.59)
60	−0.20	−1.42	−1.21	1.22	1.01	2.29	1.33	2.47	0.96	−0.19
	(−0.15)	(−3.43)	(−0.83)	(0.98)	(2.75)	(1.10)	(1.63)	(1.06)	(0.55)	(−0.36)

We sort stocks based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy is the equal-weighted portfolio of all stocks with positive excess returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. The long portfolio under the CS strategy is the equal-weighted portfolio of all stocks with returns in excess of cross-sectional mean returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. We use overlapping portfolios, like in Jegadeesh and Titman (1993), for holding periods greater than 1 month. The CS_{TVM} strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (please refer to text for details). This table reports annualized CAPM alpha in panel A and Fama and French (1993) 3-factor model alpha in panel B. Numbers in parentheses are the corresponding t-statistics. This table reports statistics for strategies with holding period equal to ranking period (corresponding to diagonal entries in Table 1) and for strategies with the holding period equal to 1 month (corresponding to entries in the first column in Table 1). We use only non-micro-cap stocks at the time of sorting. A stock is defined as non-micro-cap if it is above the 20th percentile of NYSE market capitalization. The sample period is from 1946 to 2013.

(at the least the average) of the time-varying investment in net long strategies. Accordingly, Table 4 presents the capital asset pricing model (CAPM) and Fama and French (1993) 3-factor alphas for these strategies. This analysis allows us to further assess the extent to which time-varying investment inherent in TS strategies contributes to their difference from CS strategies.

Focusing on panel A of Table 4 for CAPM alphas, the results indicate that TS alphas are significantly positive for the short ranking-period strategies, and CS alphas are significantly positive only for the 6×6, 6×1, and 12×1 strategies. CS alpha is significantly negative for the 1×1, 36×36, and 60×60 strategies, but none of the TS alphas are significantly negative. TS−CS alphas follow the same U-shaped pattern as that of returns in Table 3.

When ranking period equals holding period, the 3-factor alpha for TS$-$CS$_{\text{TVM}}$ is not different from zero for 3 $\times$ 3, 6 $\times$ 6, and 12 $\times$ 12 strategies. These are the horizons over which Jegadeesh and Titman (1993) report that momentum strategies are profitable. Therefore, when momentum works, TS strategies pick winners and losers among individual stocks in the same manner that CS strategies do. In contrast, the 3-factor alpha for TS$-$CS$_{\text{TVM}}$ is marginally positive at the short-end (1 $\times$ 1) and significantly positive at the long-end (36 $\times$ 36 and 60 $\times$ 60). Jegadeesh (1990) and De Bondt and Thaler (1985) document return reversals over these horizons. Therefore, positive alphas for these strategies TS$-$CS$_{\text{TVM}}$ indicate that CS strategies perform better if one were designing strategies to exploit short horizon and long horizon return reversals.

3. Liquidity and Higher-Order Moments

Several factors, such as liquidity, higher-order moments, and Sharpe ratios, are important considerations for investors who implement trading strategies, such as the ones we examine here. This section examines these factors for the portfolios formed using the TS and CS approaches.

3.1 Liquidity

Large investors typically implement their trading strategies with stocks that have sufficient liquidity to absorb their trades without large price impacts. This section compares liquidity-related characteristics of the long and short sides of the TS and CS portfolios. We consider the following characteristics that the literature has shown are related to liquidity: firm size, turnover, volatility, and Amihud illiquidity. Size is market capitalization at the end of the ranking period, turnover is the ratio of number of shares traded to number of shares outstanding over the last month of the ranking period, volatility is total return volatility calculated using daily data over the last month of the ranking period, and Amihud illiquidity is Amihud (2002) illiquidity measure calculated using data over the last month. Since characteristics such as firm size are highly skewed, we calculate average cross-sectional decile ranks rather than average characteristics. The decile ranks for each characteristic are computed using NYSE cutoffs.

These characteristics are also related to the ease of shorting stocks, and, hence, they also provide a perspective on the relative difficulty of implementing the short sides of the TS and CS strategies. For expositional convenience, we present the results for only the 1 $\times$ 1, 6 $\times$ 6, and 60 $\times$ 60 strategies, which are most commonly discussed in the literature. We present the results for only the TS and the CS strategy. If investors desire the time-varying market component of the CS$_{\text{TVM}}$ strategy, then they can invest in the most liquid market ETFs or stock index futures, and, therefore, the liquidity characteristics of the CS$_{\text{TVM}}$ strategy would be similar to that of the CS strategy.

Table 5
Liquidity characteristics of portfolios based on time-series and cross-sectional strategies

	1 × 1 strategy				6 × 6 strategy				60 × 60 strategy			
	TS		CS		TS		CS		TS		CS	
	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
# of stocks	829	727	722	834	878	623	653	849	770	283	346	707
Size rank	6.06	5.90	6.02	5.97	6.15	5.82	6.07	5.97	6.48	5.80	6.40	6.25
Turnover rank	5.68	5.68	5.81	5.63	5.67	5.79	5.90	5.56	5.64	5.85	5.96	5.52
Volatility rank	5.22	5.52	5.41	5.46	5.21	5.59	5.51	5.35	4.98	5.71	5.48	4.96
Amihud rank	4.92	5.17	4.94	5.11	4.84	5.19	4.87	5.12	4.67	5.01	4.70	4.80
Portfolio turnover (%)	195		207		69		79		20		28	

We sort stocks based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy is the equal-weighted portfolio of all stocks with positive excess returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. The long portfolio under the CS strategy is the equal-weighted portfolio of all stocks with returns in excess of cross-sectional mean returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. We use overlapping portfolios, like in Jegadeesh and Titman (1993), for holding periods greater than 1 month. This table presents liquidity related characteristics of for strategies in which ranking and holding periods are equal to 1, 6, and 60 months. We report decile ranks (on a scale of one to ten) for size, turnover, volatility, and Amihud illiquidity. Size is market capitalization, turnover is share turnover, volatility is total return volatility calculated using daily data over the last month, and Amihud illiquidity is the Amihud (2002) illiquidity measure calculated using data over the last month of the ranking period. The ranks are calculated based on NYSE breakpoints. The last row reports portfolio turnover. We use only non-micro-cap stocks at the time of sorting. A stock is defined as non-micro-cap if it is above the 20th percentile of NYSE market capitalization. The sample period is from 1946 to 2013.

Table 5 reports the number of stocks on the long and the short sides of the TS and CS strategies. A real-life investor may take opposite positions to our labels depending on the horizons. For example, the investor would switch positions for the 1 × 1 CS strategy. To avoid any ambiguity, we label the sides of the portfolios based on the signs of stock returns during the ranking period, relative to the thresholds.

For the 1 × 1 strategy, the TS approach on average has 829 and 727 stocks on the long and short sides, compared with 722 and 834 for the CS approach. The TS strategy has fewer stocks on the short side because its zero excess returns threshold is smaller than the cross-sectional average return threshold for the CS approach. The CS strategy has more stocks on the short side than on the long side because of the positive skewness in the cross-sectional distribution of stock returns. These differences increase with the length of the ranking period because of bigger risk premiums and bigger skewness. In all cases, there are hundreds of stocks on both sides.

Table 5 also presents the liquidity characteristics of the long and the short sides. For the 1 × 1 strategy, the size ranks for the long sides of TS and CS are 6.06 and 6.02, and that for the short side are 5.90 and 5.97. We also do not see an economically meaningful difference for turnover volatility and Amihud illiquidity ranks between the corresponding sides of the TS and CS strategies. The results are similar for the 6 × 6 strategies as well. For the 60 × 60 strategy, the liquidity characteristics of the long side are about the same for both TS and CS strategies. For example, the average size rank is 6.48 for TS and 6.40 for CS. However, the liquidity characteristics for the short side for TS are generally worse than that than for CS. We observe the biggest difference for the volatility rank – 5.71 for TS compared with 4.96 for TS.

The last row in Table 5 presents monthly turnovers for TS and CS strategies. The turnover is calculated as the sum of the absolute changes in the portfolio weights on individual stocks for each of the long and short sides and then summed for the two sides. The turnovers for CS strategies are generally bigger than that for TS strategies. For example, the turnover for the 1×1 strategy is 195% for TS compared to 207% for CS. Intuitively, TS strategies have a smaller turnover because they have a constant threshold for assigning stocks to the long and short sides, but CS strategies have a time-varying threshold based on cross-sectional average returns, which leads to more variability in their relative returns.

Overall, the differences between the liquidity characteristics of the stocks between the TS and CS strategies do not seem economically significant. The turnovers for the TS strategies are somewhat smaller than those for the CS strategies, but here again the differences do not seem particularly significant. In any event, for managing turnover, one would likely be better off using the various transaction cost mitigation techniques that Novy-Marx and Velikov (2016) discuss rather than implementing them incidentally by choosing between TS and CS thresholds.

3.2 Higher-order moments

This subsection examines higher-order moments, Sharpe ratios, and drawdowns of CS and TS strategies. These statistics are important from the perspective of an investor who uses them as stand-alone strategies. We also present the information ratios of these strategies, which are a useful metric for investors who may want to combine a strategy with other strategies as a part of their overall portfolio; the alpha in information ratio is calculated from CAPM.

Table 6 presents the higher-order moments for the 1×1, 6×6, and 60×60 strategies.[6] For the 1×1 strategy, the Sharpe ratios for TS, CS and CS_{TVM} are 0.23, −0.61, and 0.14, respectively. CS also has the biggest information ratio and the smallest drawdown among the three strategies. Therefore, the contrarian strategy based on the CS approach dominates the other two strategies. The TS approach suggests a momentum strategy at this horizon because it inadvertently conflates market-timing and return-reversals and, hence, fails to exploit the latter. For the 6×6 strategy, the Sharpe ratios for TS, CS, and CS_{TVM} are 0.32, 0.42, and 0.27, respectively. Here again, CS also has the biggest information ratio and the smallest drawdown. For that 60×60 strategy, the Sharpe ratios

[6] The 1×1 and 60×60 CS strategies exploit return reversals, like in Jegadeesh (1990) and De Bondt and Thaler (1985). Since the mean return for these strategies is negative, we compute the maximum drawdown of these strategies by taking the negative of the returns, essentially going long in stocks that are past losers and short in stocks that are past winners. The other statistics of these strategies are, however, computed in the usual way.

Table 6
Descriptive statistics for portfolios based on time-series and cross-sectional strategies

	1 × 1 strategy			6 × 6 strategy			60 × 60 strategy		
	TS	CS	CS_{TVM}	TS	CS	CS_{TVM}	TS	CS	CS_{TVM}
Mean	4.03	−5.09	2.85	5.79	3.90	5.75	7.71	−2.00	7.20
Median	2.07	−4.38	1.39	9.60	4.63	10.17	8.79	−2.29	8.99
SD	17.48	8.35	20.09	17.81	9.24	21.04	17.59	4.86	20.44
Sharpe ratio	0.23	−0.61	0.14	0.32	0.42	0.27	0.44	−0.41	0.35
Information ratio	0.40	−0.51	0.30	0.29	0.44	0.24	0.08	−0.70	−0.08
Skewness	0.13	−0.11	0.12	−1.70	−0.03	−1.72	−0.46	0.25	−0.45
Kurtosis	8.22	17.77	8.63	13.34	24.55	14.19	5.68	7.25	5.62
Drawdown	0.52	0.39	0.65	0.57	0.37	0.69	0.74	0.27	0.80

We sort stocks based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy is the equal-weighted portfolio of all stocks with positive excess returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. The long portfolio under the CS strategy is the equal-weighted portfolio of all stocks with returns in excess of cross-sectional mean returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. We use overlapping portfolios, like in Jegadeesh and Titman (1993), for holding periods greater than 1 month. The CS_{TVM} strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (please refer to text for details). This table reports the descriptive statistics for long minus short portfolio returns for strategies with ranking and holding periods equal to 1, 6, and 60 months. The means, medians, and standard deviations are annualized. Information ratio is calculated from the CAPM. We use only non-micro-cap stocks at the time of sorting. A stock is defined as non-micro-cap if it is above the 20th percentile of NYSE market capitalization. The sample period is from 1946 to 2013.

for these strategies are 0.44, −0.41, and 0.35. Although the Sharpe ratio for the TS strategy is marginally bigger than that for the CS strategy, the CS strategy has a bigger information ratio and a smaller drawdown.

4. Sources of TVM Excess Returns

Our results so far indicate that the larger excess returns on the time-varying net long investments in risky assets largely explain the difference between the performances of TS and CS strategies. The average risk premium earned by the TVM is one reason for this difference, but it is not the complete explanation. For instance, net long positions taken by TS strategies increase on average with the length of the ranking period, but the excess returns for TS−CS in Table 3 exhibit a U-shaped pattern. For instance, the excess returns for TS−CS is 9.12% for the 1 × 1 strategy, which is about the same as 9.71% for the 60 × 60 strategy, although the net long for the former is \$0.12 and for the latter is \$0.99. What explains this dichotomy?

Let the investment in the ith stock for the TS (CS) strategy be denoted by w_{it-1}^{TS} (w_{it-1}^{CS}). Since CS strategies are zero net investment strategies, the sum across stocks of CS investment is zero. For TS strategies, the net long position is

$$\mathrm{NetLong}_t = \sum_i w_{it-1}^{TS}. \tag{3}$$

The TVM strategy invests the net long position in the equal-weighted index. Its return is

$$R_t^{TVM} = \text{NetLong}_t \times \bar{R}_t = \sum_i w_{it-1}^{TS} \times \bar{R}_t,$$

$$R_t^{CS_{TVM}} = R_t^{CS} + R_t^{TVM}, \tag{4}$$

We can decompose the average returns to the TVM strategy as follows:

$$\overline{R_t^{TVM}} = \underbrace{\overline{\text{NetLong}_t} \times \overline{\bar{R}_t}}_{\text{Risk Premium}} + \underbrace{\text{cov}\left(\text{NetLong}_t, \bar{R}_t\right)}_{\text{Market Timing}}, \tag{5}$$

where $\overline{\text{NetLong}_t}$ and $\overline{\bar{R}_t}$ are the average net long position and the average equal-weighted excess return, respectively, over the sample period. Since the TS strategy on average invests $\overline{\text{NetLong}_t}$ in risky assets, the expected excess return for this position is given by the first term, which we refer to as the risk premium component. Since relatively more stocks are expected to have positive ranking period excess returns in upmarkets, the net long position will tend to vary positively with ranking period market returns; the net long positon will tend to be more positive following upmarkets than following downmarkets. This time-varying pattern of net long position taken by the TS strategy could add to the performance of TS strategies if future market returns drift in the same direction as the return during the ranking period (or equivalently, if market returns exhibit positive autocorrelation at the relevant horizons). We refer to this component as the market timing component.[7]

Table 7 presents the decomposition of the time-varying investment in the market. We compute the standard errors for the risk premium and the market timing components using the formulas that we derive in the appendix. The risk premium component of the difference is the equal-weighted market return on the net long position over the sample period. For example, the net long component for the 1 × 1 strategy is 0.12 times the average return of the equal-weighted index constructed with the stocks in the sample.[8] This component is significantly positive for all strategies monotonically increasing from 1.09% for the 1 × 1 strategy to 9.68% for the 60 × 60 strategy. For long ranking-period strategies, virtually all of TVM return comes from the net long positions.

The market timing component accounts for most of the TVM returns at short horizons. Specifically, this component accounts for 6.85% of 7.94%

[7] We use the term “market timing” in the sense commonly used in the mutual fund literature (see, e.g., Merton and Henriksson 1981). This literature examines whether mutual fund managers successfully time the market by increasing their market exposures prior to upmarkets and reducing their exposures prior to downmarkets.

[8] The samples of stocks each month differ slightly across ranking periods. For example, for a 1-month ranking period, we include all stocks that meet our criteria and also have 1-month returns data. For a 6-month ranking period, our past return restriction requires all stocks to have data on 6-month returns and, hence, excludes a few firms from the 1-month sample.

Table 7
Decomposition of time-varying investment in the market

	Holding period = Ranking period					Holding period = 1 month				
Ranking period	TVM	Risk premium	Market timing	$Net long	Equal-weighed return	TVM	Risk premium	Market timing	$Net long	Equal-weighed return
1	7.94	1.09	6.85	0.12	8.80	7.94	1.09	6.85	0.12	8.80
	(4.18)	(2.70)	(3.48)	(4.15)	(4.08)	(4.18)	(2.70)	(3.48)	(4.15)	(4.08)
3	3.13	2.43	0.70	0.27	8.90	5.73	2.42	3.31	0.28	8.80
	(1.80)	(3.78)	(0.38)	(9.95)	(4.13)	(2.85)	(3.59)	(1.59)	(8.54)	(4.09)
6	1.86	3.22	−1.37	0.36	8.97	4.95	3.22	1.73	0.36	8.86
	(0.98)	(3.99)	(−0.72)	(13.17)	(4.16)	(2.32)	(3.82)	(0.77)	(11.10)	(4.14)
12	1.16	4.35	−3.19	0.48	9.10	4.44	4.33	0.11	0.48	8.99
	(0.62)	(4.20)	(−1.76)	(18.59)	(4.24)	(1.99)	(4.06)	(0.05)	(15.13)	(4.23)
36	6.37	7.63	−1.25	0.79	9.63	5.20	7.33	−2.13	0.78	9.38
	(3.27)	(4.58)	(−0.99)	(36.71)	(4.60)	(2.37)	(4.47)	(−1.01)	(28.46)	(4.50)
60	9.20	9.68	−0.48	0.99	9.74	7.44	9.08	−1.64	0.96	9.49
	(4.16)	(4.73)	(−0.43)	(47.93)	(4.75)	(3.20)	(4.61)	(−0.85)	(37.54)	(4.63)

This table reports the decomposition of the time-varying investment in the market (TVM) into the two components related to risk premium and market timing (please refer to text for details). We first form portfolios using time-series (TS) strategies, where the long portfolio is the equal-weighted portfolio of all stocks with positive excess returns during the ranking period and the short portfolio is the equal-weighted portfolio of the other stocks. We use overlapping portfolios, like in Jegadeesh and Titman (1993), for holding periods greater than 1 month. $Net long is average net long position (in dollars) of the time-series strategy, while Equal-weighted return is the average annualized holding period return on an equal-weighted index of stocks included in the portfolio sorts. Numbers in parentheses are the corresponding t-statistics. This table reports statistics for strategies with holding period equal to ranking period (corresponding to diagonal entries in Table 1) and for strategies with the holding period equal to 1 month (corresponding to entries in the first column in Table 1). We use only non-micro-cap stocks at the time of sorting. A stock is defined as non-micro-cap if it is above the 20th percentile of NYSE market capitalization. The sample period is from 1946 to 2013.

TVM return for 1×1 strategy. The finding that this component is positive indicates that when the TS strategy takes a more active long position in the ranking period, the market returns is on average positive during the holding period. The correlation between the net long investment and the equal-weighted index return during the ranking period is 92%, and the first-order serial correlation of the equal-weighted index return is 14%; the source of the market timing component is this latter correlation.

Thus, different aspects of investments in the market portfolio account for the U-shaped returns earned by TVM. For the 1×1 strategy, the difference is due to market timing. Specifically, the TS strategy invests more in the market index following an upmarket and less following a down-market, thereby exploiting the positive serial correlation in index returns. For the long ranking-period strategies, such as the 60×60 strategies, the TS strategy benefits from the risk premium component due to large net long position in the market.

We also examine whether the profitability of TVM is related to macroeconomic variables that predict market returns. The macroeconomic variables we choose are dividend-price ratio, default spread, term spread, and 3-month Treasury-bill yields, which are the most commonly used variables to predict market returns in the literature (see Rapach and Zhou 2013 for a recent survey). In the results tabulated in Internet Appendix Table A2.1, we find that, with a few exceptions, macro variables have limited power for forecasting

TVM. Therefore, the profitability of TVM returns is only marginally related to macroeconomic factors.

5. International Asset Classes

The literature sometimes finds differences in the performances of TS and CS strategies with international asset classes (e.g, MOP 2012; Menkhoff et al. 2012). Our analysis with individual U.S. stocks also finds differences between the performances of TS and CS strategies, but also shows that these differences are entirely attributable to the underlying pattern of investments in the aggregate market inherent in the TS strategies. This section compares the performance of TS and CS strategies with international assets.

5.1 Data

We obtain daily settlement prices for 55 futures markets for 1985 to 2013 from Commodity Systems, Inc. These futures contracts are the same as those used in Kim, Tse, and Wald (2016) and comparable to the data used by MOP (2012). These futures contracts represent four broad asset classes of equities, bonds, commodities, and currencies. We refer the reader to Kim, Tse, and Wald for further details on these contracts. We compute the daily excess returns as percentage changes using the nearest contracts (until the first trading day of the maturity month), and then roll over to the second-nearest contracts within the delivery month. Monthly excess returns are calculated by compounding the daily excess returns.[9]

We present descriptive statistics on the average excess return (constructed as the equal-weighted average of all available assets) for each asset class in Table 8. The average return on all asset classes is high during our sample period. Unsurprisingly, equity returns have a higher standard deviation than currency returns. We also report correlations between past and future returns for horizons of 1, 3, 12, and 60 months. The correlations are generally positive for shorter horizons, but negative for horizons of 60 months. This means that a market timing strategy conditioned on past average returns will be profitable for shorter horizons, but will lose money for a longer horizon. However, the statistical significance of these correlations is low. The only exception is equities, where 1-month correlation of 0.12 and 60-month correlation of −0.15 are statistically significant.

5.2 TS and CS strategies

We examine two categories of TS and CS strategies with asset classes. The first category is the same as before, where the long side is an equal-weighted portfolio of all assets with positive excess returns (in excess of zero for TS

---

[9] We thank Yiuman Tse, who helped compute futures returns.

Table 8
Descriptive statistics for asset classes

	All	Equities	Bonds	Commodities	Currencies
Mean	5.56	6.32	3.12	7.04	3.19
	(3.78)	(2.11)	(3.75)	(2.80)	(2.06)
Median	6.62	15.50	2.87	8.43	2.46
	(3.59)	(4.13)	(2.76)	(2.68)	(1.27)
SD	7.93	16.14	4.48	13.54	8.34
$\rho_{(1)}$	0.04	0.10	0.12	0.09	0.03
	(0.67)	(1.93)	(2.17)	(1.62)	(0.58)
$\rho_{(3)}$	0.09	0.07	0.04	0.10	0.11
	(1.71)	(1.37)	(0.71)	(1.83)	(2.07)
$\rho_{(12)}$	−0.01	0.05	0.03	0.01	0.06
	(−0.13)	(0.84)	(0.46)	(0.26)	(1.05)
$\rho(60)$	−0.09	−0.11	−0.15	−0.05	0.03
	(−1.57)	(−1.85)	(−2.54)	(−0.84)	(0.54)

We present descriptive statistics on excess returns on the equal-weighted portfolios of various asset classes. Means, medians, and standard deviation are annualized and reported in percent per month. $\rho(k)$ is the correlation between returns over prior k months and the future month. Numbers in parentheses are the corresponding t-statistics. Details on asset classes are provided in the text. The sample period is from 1985 to 2013.

strategies and in excess of the cross-sectional mean for CS strategies) and the short side is an equal-weighted portfolio of all remaining assets. We refer to these strategies as unscaled strategies.

The second category, which we refer to as scaled strategies, follows the inverse volatility scaling approach that MOP (2012) use. The scaled TS strategies scale the position in each asset by a factor equal to 40% divided by the lagged volatility of the asset.[10] Thus, the return to the scaled TS strategy is given by

$$R_t^{TS,scaled} = \frac{1}{N}\sum_i \text{sign}(R_{it-1}) \times \frac{40\%}{\sigma_{it-1}} \times R_{it}, \tag{6}$$

where R_{it-1} is the ranking period excess return on the ith asset and σ_{it-1} is its lagged volatility. We follow MOP in estimating σ_{it-1} as the exponentially weighted average of lagged squared daily returns as

$$\sigma_{it-1}^2 = 261\sum_{s=0}^{\infty}(1-\delta)\delta^s(R_{it-1-s} - \bar{R}_{it-1})^2, \tag{7}$$

where the sum of weights add up to one, the parameter δ is chosen so that the center of mass of weights is equal to 60 days ($\delta/(1-\delta)=60$), and the average return $\bar{R}_{it-1}$ is also calculated as the exponentially weighted average using the same weights. The dollar long and short positions of the scaled TS strategy are given by

$$\$\text{Long}_t^{TS,scaled} = \frac{1}{N}\sum_{R_{it-1}\geqslant 0}\frac{40\%}{\sigma_{it-1}} \text{ and } \$\text{Short}_t^{TS,scaled} = \frac{1}{N}\sum_{R_{it-1}<0}\frac{40\%}{\sigma_{it-1}}. \tag{8}$$

[10] MOP (2012) use a constant 40% in the numerator "because it is similar to the risk of an average individual stock," and we use the same scaling constant.

While the sum of investment on the long plus short sides equals \$2 for the unscaled strategies, the total investment varies inversely with the standard deviations of the assets, and it is always bigger than \$2 in our sample because of volatility scaling.[11]

We construct scaled CS strategies to compare with scaled TS strategies. First, as before, all assets with excess return greater than or equal to the cross-sectional average returns during the ranking period are in the long portfolio and the others are in the short portfolio. We then weight each asset i inversely proportional to σ_{it-1}. Finally, to equate the total active positions of the TS and CS strategies, we set the dollar value of each side for month t equal to $(\$\mathrm{Long}_t^{TS,scaled}+\$\mathrm{Short}_t^{TS,scaled})/2$. Thus, the return to the scaled CS strategy is given by

$$R_t^{CS,scaled}=\left(\frac{\$\mathrm{Long}_t^{TS,scaled}+\$\mathrm{Short}_t^{TS,scaled}}{2}\right)$$
$$\times\left[\frac{\sum_{R_{it-1}\geqslant\bar{R}_{t-1}}\frac{40\%}{\sigma_{it-1}}\times R_{it}}{\sum_{R_{it-1}\geqslant\bar{R}_{t-1}}\frac{40\%}{\sigma_{it-1}}}-\frac{\sum_{R_{it-1}<\bar{R}_{t-1}}\frac{40\%}{\sigma_{it-1}}\times R_{it}}{\sum_{R_{it-1}<\bar{R}_{t-1}}\frac{40\%}{\sigma_{it-1}}}\right]. \tag{9}$$

As with unscaled strategies, the scaled TS strategies end up with a time-varying net long position, but scaled CS strategies have a zero net long position. The net long position for the TS strategies in month t equals $(\$\mathrm{Long}_t^{TS,scaled}-\$\mathrm{Short}_t^{TS,scaled})$.[12] To put scaled TS and CS strategies on a common footing, we add a time-varying investment in a scaled market index to the scaled CS strategies and construct scaled $\mathrm{CS_{TVM}}$ strategies. We construct the scaled market index $\bar{R}_t^{scaled}$ as follows

$$\bar{R}_t^{scaled}=\frac{\sum_i\frac{40\%}{\sigma_{it-1}}\times R_{it}}{\sum_i\frac{40\%}{\sigma_{it-1}}},\ \text{and}\ R_t^{CS_{TVM},scaled}=R_t^{CS,scaled}$$
$$+(\$\mathrm{Long}_t^{TS,scaled}-\$\mathrm{Short}_t^{TS,scaled})\times\bar{R}_t^{scaled}. \tag{10}$$

---

11 We also examine a similar inverse volatility scaled strategy with individual stocks. The average long plus short investment for this scaled strategy is \$1.6 compared with \$2 for unscaled strategies (Table 3). Therefore, the magnitude of returns is a bit smaller for scaled strategies than that for unscaled strategies. Otherwise, in Table 3, we find that the untabulated results are qualitatively similar to that for unscaled strategies with individual stocks.

12 Because of inverse volatility scaling, the total active investment (\$long + \$short) for scaled TS strategies is bigger in low-volatility periods than in high-volatility periods. Such time variation is an incidental feature of TS strategies, but Barroso and Santa-Clara (2015) and Moreira and Muir (2017) show that inverse volatility scaling increases the Sharpe ratios of CS momentum strategies and other anomalies.

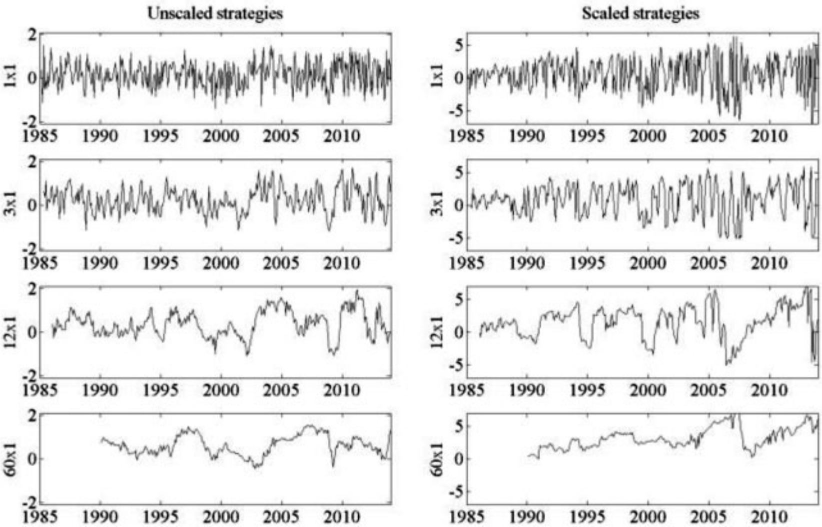

Figure 2
Net long positions for time-series strategies with international asset classes
The long portfolio under the TS strategy comprises all assets with positive excess returns during the ranking period, and the short portfolio comprises the other assets. The scaled strategies scale portfolio weights based on past realized volatility of each asset (please see text for details). Portfolios are held for 1 month. The figure shows the net long position (in dollars) for these strategies each month (the y-axis scale is different in the figures for scaled and unscaled strategies). The sample period is from 1985 to 2013.

5.3 All asset classes

5.3.1 Excess returns. Panel A of Table 9 presents the returns to TS and CS strategies with a pooled sample of all asset classes. Because we now have unscaled and unscaled versions of TS and CS strategies, we report the results for only ranking periods of 1, 3, 12, and 60 months and for a holding period of 1 month for brevity. The excess returns are positive and statistically significant for both unscaled CS and TS strategies for all but the 60×1 strategy. For example, unscaled TS and CS returns for the 12×1 strategy are 10.23% and 9.86%, respectively. The differences between the excess returns to the unscaled TS and the CS strategies are not significantly different from zero.

The left four panels of Figure 2 present the net long positions for the unscaled TS strategies. The monthly net long positions vary significantly over time, ranging from −\$1.40 to \$1.50 for the 1×1 strategy, −\$1.09 to \$1.93 for the 12×1 strategy, and −\$0.46 to \$1.56 for the 60×1 strategy. The average net long positions are all positive, ranging from \$0.15 for the 1×1 strategy to \$0.63 for the 60×1 strategy.

The asset classes in the sample earn positive excess returns on average and, hence, the net long positon would add to the excess returns for the TS strategies relative to the CS strategies. The excess returns for all unscaled CS_{TVM} strategies in panel A of Table 9 are bigger than those for the corresponding

Table 9
Portfolio returns and average asset allocation based on time-series and cross-sectional strategies with all asset classes

A. Excess returns

	Unscaled strategies							Scaled strategies						
Ranking period	TS	CS	CS_{TVM}	TS−CS	$TS-CS_{TVM}$	\$Long	\$Short	TS	CS	CS_{TVM}	TS−CS	$TS-CS_{TVM}$	\$Long	\$Short
1	6.77	6.60	7.57	0.16	−0.80	1.08	−0.92	9.33	13.13	14.27	−3.80	−4.94	2.82	−2.20
	(2.95)	(2.94)	(2.71)	(0.16)	(−0.78)	(4.75)	(4.75)	(4.35)	(3.13)	(3.22)	(−1.29)	(−1.64)	(23.82)	(−15.41)
3	9.18	8.47	11.00	0.70	−1.83	1.11	−0.89	11.83	17.55	19.90	−5.72	−8.07	2.90	−2.11
	(3.99)	(3.78)	(4.01)	(0.67)	(−2.01)	(7.49)	(7.49)	(5.31)	(4.01)	(4.50)	(−1.87)	(−2.79)	(25.67)	(−14.62)
12	10.23	9.86	12.60	0.36	−2.37	1.19	−0.81	14.75	21.55	26.13	−6.80	−11.38	3.28	−1.73
	(4.38)	(3.99)	(4.06)	(0.32)	(−1.82)	(11.58)	(11.58)	(6.52)	(4.36)	(4.91)	(−1.95)	(−3.04)	(28.81)	(−10.18)
60	1.25	1.36	3.15	−0.11	−1.90	1.31	−0.69	4.30	4.17	11.43	0.13	−7.13	4.16	−0.95
	(0.56)	(0.53)	(0.90)	(−0.08)	(−1.02)	(23.18)	(23.18)	(1.88)	(0.79)	(1.84)	(0.03)	(−1.43)	(37.08)	(−2.58)

(*continued*)

Table 9
Continued

B. Average allocation to asset classes

	TS				CS			
Ranking period	Equities	Bonds	Commodities	Currencies	Equities	Bonds	Commodities	Currencies
	Unscaled strategies							
	$Long							
1	0.18	0.25	0.49	0.16	0.17	0.18	0.51	0.14
3	0.19	0.26	0.50	0.17	0.18	0.17	0.51	0.14
12	0.20	0.31	0.50	0.18	0.19	0.16	0.52	0.13
60	0.18	0.39	0.55	0.19	0.14	0.18	0.60	0.09
	$Short							
1	−0.13	−0.18	−0.48	−0.14	−0.14	−0.20	−0.51	−0.15
3	−0.12	−0.17	−0.47	−0.13	−0.14	−0.21	−0.51	−0.15
12	−0.11	−0.12	−0.47	−0.11	−0.14	−0.21	−0.50	−0.15
60	−0.13	−0.02	−0.44	−0.10	−0.16	−0.20	−0.48	−0.17
	Scaled strategies							
	$Long							
1	0.21	1.84	0.42	0.34	0.34	1.04	0.74	0.39
3	0.23	1.89	0.43	0.35	0.39	0.96	0.76	0.41
12	0.25	2.22	0.42	0.39	0.52	0.78	0.82	0.38
60	0.21	3.09	0.45	0.41	0.29	0.94	1.05	0.27
	$Short							
1	−0.14	−1.35	−0.42	−0.29	−0.22	−1.21	−0.69	−0.38
3	−0.12	−1.30	−0.42	−0.27	−0.19	−1.26	−0.67	−0.38
12	−0.09	−0.97	−0.43	−0.24	−0.18	−1.37	−0.62	−0.33
60	−0.14	−0.17	−0.42	−0.22	−0.17	−1.51	−0.49	−0.39

We sort assets based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy comprises all assets with positive excess returns during the ranking period, and the short portfolio comprises the other assets. The long portfolio under the CS strategy comprises all assets with returns in excess of cross-sectional mean returns during the ranking period, and the short portfolio comprises the other assets. The unscaled strategies form equal-weighted long and short portfolios. The scaled strategies scale portfolio weights based on past realized volatility of each asset (please see text for details). Portfolios are held for 1 month. The $\mathrm{CS}_{\mathrm{TVM}}$ strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (please refer to text for details). The table reports long minus short portfolio excess returns. Panel A reports the annualized excess returns to these strategies. $Long and $Short are the average dollar positions of the TS strategy. Numbers in parentheses are the corresponding t-statistics (t-statistics for $Long and $Short are calculated for the null of $1 and −$1, respectively). Panel B reports the average dollar long and dollar short allocation to the four asset assets, viz. equities, bonds, commodities, and currencies. Details on asset classes are provided in the text. The sample period is from 1985 to 2013.

TS strategies. The differences between the excess returns are 1.83% and 2.37% for the 3 × 1 and 12 × 1 strategies, and are statistically significant at the five and ten percent levels, respectively.

Table 9 also presents the results for scaled TS and CS strategies. Both scaled TS and CS strategies earn positive excess returns for all ranking periods, as is the case of unscaled strategies. However, the magnitudes of the excess returns for the strategies are quite different. For example, the excess returns for the 12 × 1 scaled TS strategies is 14.75% compared with 21.55% for the scaled CS strategy. The scaled CS strategies earn bigger returns than the corresponding TS strategies for all ranking periods except the 60 × 1 strategy.

The net long positions for the scaled TS strategies are significantly higher than those for the unscaled TS strategies. The right four panels of Figure 2 present the net long positions for the scaled TS strategies each month. The monthly net long positions vary significantly over time, ranging from −\$7.25 to \$6.39 for the 1 × 1 strategy, −\$5.08 to \$8.18 for the 12 × 1 strategy, and \$0.00 to \$8.01 for the 60 × 1 strategy. The average net long position increases from \$0.62 for the 1 × 1 strategy to \$3.21 for the 60 × 1 strategy.

The excess returns to the scaled CS_{TVM} are significantly bigger than that for the corresponding scaled TS strategies for all ranking periods. For example, the excess returns for the 12 × 1 scaled TS and CS_{TVM} strategies are 14.75% and 26.13% and the t-statistic for the difference is 3.04.

Figure 3 presents the cumulative returns on the 12 × 1 scaled TS, CS, and CS_{TVM} strategies on a log scale. The investment of \$1 at the beginning of the sample period grows to \$50, \$154, and \$456 for the three strategies, respectively. The large difference reflects the superior performance of CS and CS_{TVM} strategies in Table 9. However, the TS strategy is much less volatile, particularly during the great recession period, because of its bigger investment in bonds, as we explain below.

To further understand the underlying sources of the difference, we examine the average portfolio weights assigned to each asset class under the different strategies. Panel B of Table 9 presents the results. For the unscaled CS strategies, the average net weights are generally close to zero, and they range from −5% to +5% for all strategies except the 60 × 1 strategy. These results indicate that each asset class is almost as likely to be on the long side like in the short side for the unscaled CS strategies. For the unscaled TS strategies, the weights for all asset classes are on average positive due to the fact that the average net long position is positive. The average weights vary significantly across asset classes. For example, for 12 × 1 the average net investment in bonds is \$0.19(=\$0.31−\$0.12) compared with \$0.03(=\$0.50−\$0.47) for commodities. The average weights for bonds are bigger than that for other classes for all ranking periods, reflecting the fact that indices are more likely to be positive than negative than other asset classes during our sample period.

The average investments deviate further from zero for most of the scaled strategies than the corresponding unscaled strategies. The scaled TS strategies

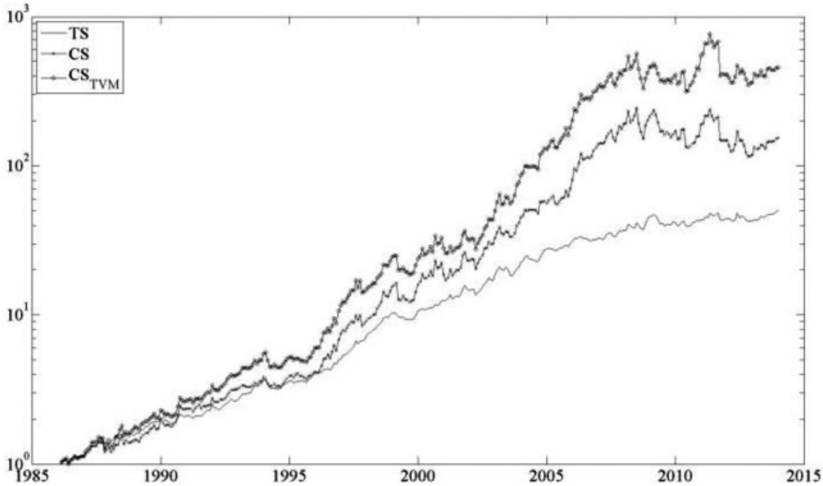

Figure 3
Cumulative growth of $1 for 12 × 1 scaled strategies with international asset classes
We sort asset classes based on prior returns during a ranking period of 12 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. We scale the portfolio weights based on past realized volatility. Portfolios are kept for a holding period of 1 month. The CS_{TVM} strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (refer to the text for details). The figure plots the cumulative growth of $1 invested at the beginning of the sample period on a log scale. The sample period is from 1985 to 2013.

assign large positive weights to bonds for all ranking periods. The average net investment increases from $0.49 for the 1 × 1 strategy to $2.92 for the 60 × 1 strategy. In contrast, the scaled CS strategies assign negative weights ranging from −$0.17 to −$0.57 for bonds.

Arbitrage strategies typically attempt to identify overpriced and underpriced asset classes. If assets are on average fairly priced then overpricing and underpricing would be equally likely and, hence, assets should be equally likely to enter the long and short sides. We see this property for the unscaled CS strategies. In contrast, TS strategies show a strong tendency to invest in bonds. The preference for bonds is significantly magnified for the scaled strategies because they have the lowest volatility among all asset classes. TS strategies are long bonds during most of the sample period because the likelihood of negative excess return is relatively low. This property is a description of the distribution of bond index excess returns, and it is hard to view it as an indicator for persistent underpricing. If one had a preference for bonds, then one could choose a bond heavy strategy by design rather than inadvertently ending up with such a strategy by following a scaled TS approach.

5.3.2 Alpha. We next examine risk-adjusted returns for TS and CS strategies. We use the same factor model as MOP (2012) and include the U.S. market, SMB, HML, UMD, an aggregate bond factor (Barclays global aggregate bond factor),

Table 10
Portfolio alphas based on time-series and cross-sectional strategies with all asset classes

	Unscaled strategies					Scaled strategies				
Ranking period	TS	CS	CS_{TVM}	TS−CS	TS−CS_{TVM}	TS	CS	CS_{TVM}	TS−CS	TS−CS_{TVM}
1	7.68	6.95	8.54	0.73	−0.86	9.28	14.53	14.41	−5.25	−5.13
	(3.19)	(2.92)	(2.89)	(0.66)	(−0.80)	(4.12)	(3.30)	(3.06)	(−1.69)	(−1.61)
3	9.02	7.90	10.79	1.12	−1.77	10.77	17.83	18.09	−7.06	−7.32
	(3.81)	(3.43)	(3.82)	(1.03)	(−1.93)	(4.63)	(3.94)	(3.95)	(−2.22)	(−2.44)
12	7.90	7.55	9.23	0.35	−1.33	10.70	16.79	18.32	−6.09	−7.62
	(3.56)	(3.18)	(3.13)	(0.30)	(−1.08)	(5.04)	(3.52)	(3.61)	(−1.79)	(−2.14)
60	−2.21	−0.14	−0.38	−2.07	−1.84	−1.93	−0.54	1.73	−1.40	−3.66
	(−1.16)	(−0.07)	(−0.14)	(−1.55)	(−1.33)	(−1.07)	(−0.12)	(0.36)	(−0.39)	(−0.96)

We sort assets based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy comprises all assets with positive excess returns during the ranking period, and the short portfolio comprises the other assets. The long portfolio under the CS strategy comprises all assets with returns in excess of cross-sectional mean returns during the ranking period, and the short portfolio comprises the other assets. The unscaled strategies form equal-weighted long and short portfolios. The scaled strategies scale portfolio weights based on past realized volatility of each asset (please see text for details). Portfolios are held for 1 month. This table reports annualized alphas for the long minus short portfolios. The CS_{TVM} strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (please refer to text for details). Alphas are calculated from a factor model that includes the Fama and French (1993) U.S.-based three factors, the Carhart (1997) momentum factor, the Barclays Global aggregate bond factor, and the S&P Commodities GSCI factor. Numbers in parentheses are the corresponding t-statistics. The sample period is from 1985 to 2013.

and a commodity factor (S&P commodities GSCI factor). Table 10 presents the alphas from this factor model. For both the scaled and unscaled strategies, the alphas for the 1×1 and 3×1 strategies are about the same as the corresponding excess returns. For example, for the 3×1 strategies, the excess returns for the unscaled TS and CS strategies are 9.18% and 8.47%, compared with alphas of 9.02% and 7.90%, respectively. The alphas for longer ranking periods, however, are significantly smaller than the corresponding excess returns for the TS, CS, and CS_{TVM} strategies. For example, for the 12×1 strategies, the returns on scaled TS, CS, and CS_{TVM} are 14.75%, 21.55%, and 26.13%, compared with alphas of 10.70%, 16.79%, and 18.32%, respectively.

The asset class composition of the portfolios and the net long positions of TS strategies vary significantly over time and, hence, portfolio betas would also vary over time. If the risk premia for various asset classes also vary over time, then such variation, in conjunction with time-varying betas, would lead to model misspecification. To address such concerns we consider a second procedure to adjust for risk. For each asset, we compute abnormal returns as the asset return minus the return on the equal-weighted index of all assets in that asset class. In untabulated results, we find that this approach also yields qualitatively similar results. Specifically, we find that except for the 60×1 strategy, all alphas are statistically significant and the alphas for both scaled CS and CS_{TVM} are significantly bigger than that for corresponding scaled TS strategies. Overall, these results indicate that unscaled TS and CS perform similarly, but scaled CS strategies outperform scaled TS strategies.

Table 11
Descriptive statistics for portfolios based on time-series and cross-sectional strategies with all asset classes

	Unscaled strategies			Scaled strategies		
	TS	CS	CS_{TVM}	TS	CS	CS_{TVM}
			1 × 1 strategy			
Mean	6.77	6.60	7.57	9.33	13.13	14.27
Median	6.02	6.01	5.96	8.38	13.16	14.55
SD	12.33	12.08	15.03	11.53	22.53	23.83
Sharpe ratio	0.55	0.55	0.50	0.81	0.58	0.60
Skewness	0.97	0.54	0.87	0.19	0.29	−0.01
Kurtosis	9.07	5.07	8.23	4.09	4.79	3.80
Drawdown	0.26	0.29	0.37	0.17	0.44	0.43
			3 × 1 strategy			
Mean	9.18	8.47	11.00	10.60	14.60	16.92
Median	7.22	6.35	6.04	10.60	14.60	16.92
SD	12.33	12.02	14.70	11.96	23.46	23.70
Sharpe ratio	0.74	0.70	0.75	0.99	0.75	0.84
Skewness	1.15	0.33	0.81	0.12	0.25	−0.05
Kurtosis	10.30	4.99	8.11	4.35	5.35	4.26
Drawdown	0.13	0.27	0.22	0.18	0.43	0.40
			12 × 1 strategy			
Mean	10.23	9.86	12.60	14.75	21.55	26.13
Median	10.25	8.12	12.19	15.58	23.28	29.48
SD	12.36	13.08	16.40	11.97	26.14	28.18
Sharpe ratio	0.83	0.75	0.77	1.23	0.82	0.93
Skewness	−0.26	0.19	−0.36	−0.11	−0.25	−0.53
Kurtosis	4.58	5.65	5.63	3.21	4.90	5.76
Drawdown	0.34	0.21	0.33	0.17	0.53	0.55
			60 × 1 strategy			
Mean	−1.04	0.16	−1.03	4.30	4.17	11.43
Median	2.14	2.67	5.72	5.23	2.34	7.57
SD	10.86	12.56	17.20	11.22	25.90	30.47
Sharpe ratio	0.12	0.11	0.18	0.38	0.16	0.38
Skewness	−1.04	0.16	−1.03	−0.31	0.25	0.05
Kurtosis	9.79	6.34	13.47	4.12	8.41	8.85
Drawdown	0.44	0.44	0.65	0.36	0.74	0.77

We sort assets based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy comprises all assets with positive excess returns during the ranking period, and the short portfolio comprises the other assets. The long portfolio under the CS strategy comprises all assets with returns in excess of cross-sectional mean returns during the ranking period, and the short portfolio comprises the other assets. The unscaled strategies form equal-weighted long and short portfolios. The scaled strategies scale portfolio weights based on past realized volatility of each asset (please see text for details). Portfolios are held for 1 month. The CS_{TVM} strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (please refer to text for details). We report the characteristics of long minus short portfolio returns for TS and CS strategies. The means, medians, and standard deviations are annualized. The sample period is from 1985 to 2013.

5.4 Higher-order moments for all asset classes

Table 11 presents the higher-order moments for the TS, CS and CS_{TVM} strategies. Unscaled TS and CS strategies have similar volatilities, but CS_{TVM} has bigger volatilities. The Sharpe ratios of TS and CS_{TVM} are similar. Overall, we do not see a big difference in the various performance measures among the three unscaled strategies although the asset compositions of TS and CS strategies are somewhat different.

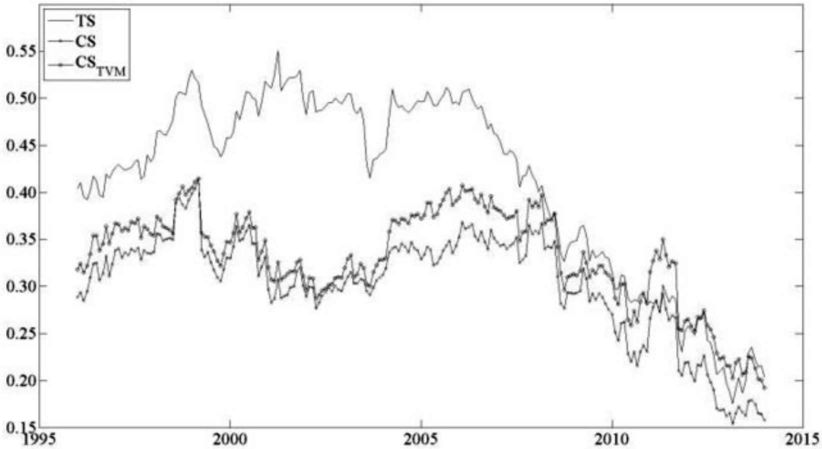

Figure 4
Rolling 10-year Sharpe ratios for 12 × 1 scaled strategies with international asset classes
We sort asset classes based on prior returns during a ranking period of 12 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. We scale the portfolio weights based on past realized volatility. Portfolios are kept for a holding period of 1 month. The CS_{TVM} strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (refer to the text for details). The figure plots rolling 10-year Sharpe ratios of these strategies. The sample period is from 1985 to 2013.

The median returns for the scaled TS strategies are all smaller than the corresponding CS and CS_{TVM}. For example, the median returns for the 12×1 strategies for TS, CS, and CS_{TVM} are 15.58%, 23.28%, and 28.18%, respectively. The standard deviations and drawdowns are smaller, and Sharpe ratios are bigger for TS strategies than for CS and CS_{TVM} strategies. For example, their Sharpe ratios for the 12×1 strategies are 1.23, 0.82, and 0.93, respectively. Figure 4 plots the rolling 10-year Sharpe ratios for these three strategies. The Sharpe ratios exhibit particularly large differences during the early years, but they are all about equal during the latter part of the sample period. Similarly, drawdown for 12×1 TS, CS, and CS_{TVM} strategies are 0.17, 0.53, and 0.55, respectively. The smaller drawdowns and bigger Sharpe ratios would make TS strategies more attractive than CS strategies for investors who plan to choose one of the two as a stand-alone strategy.

These results indicate that the scaled TS strategies are less risky than the CS strategies when we use multiple asset classes that include bonds. As we discussed earlier, scaled TS strategies have a strong tendency to invest in bonds and bonds have the smallest risk and biggest Sharpe ratio among all the asset classes in the sample (see Table 8). TS strategies tilt towards bonds because this asset class experiences positive excess returns more often than other asset classes. While the scaled TS strategy incidentally picks safer portfolios because of the bond return distribution, it is likely that strategies that specifically seek to manage volatility across multiple asset classes (similar to those in

Barroso and Santa-Clara 2015 and Moreira and Muir 2017) would result in portfolios that are closer to investors' objectives.

5.5 Individual asset classes

Table 12 reports the excess returns for TS and CS strategies within individual asset classes. For equities in panel A, the unscaled 1×1 CS strategy earns marginally significant negative excess returns indicating that indices that underperform the average in 1 month tend to outperform the following month. All the other scaled and unscaled CS strategies earn insignificant excess returns and with almost equal numbers of positive and negative point estimates.

In contrast, the excess returns for both scaled and unscaled TS equities strategies are mostly positive. For example, the scaled and unscaled 12×1 TS and CS_{TVM} strategies, which have the same net long position as the corresponding TS strategies, earn significantly positive excess returns. However, the excess returns for the TS and the corresponding CS_{TVM} strategies are not statistically different for any ranking period. The average net long positions for the TS strategies are all significantly positive.

For currencies in panel B of Table 12, the excess returns for both the unscaled and scaled CS strategies are positive for all ranking periods other than sixty months, albeit not statistically significantly so. In contrast, the scaled and unscaled TS strategies earn significantly positive returns for all ranking periods other than sixty months, and CS_{TVM} strategies perform similarly. For commodities in panel C, scaled and unscaled TS, CS, and CS_{TVM} strategies earn positive returns for all ranking periods; the returns are statistically significant for short ranking periods. For all strategies with currencies and commodities, the excess returns for the TS and the corresponding CS_{TVM} strategies are not statistically different.

With bond indices in panel D, unscaled CS strategies mostly earn insignificant returns, but unscaled TS and CS_{TVM} strategies earn significantly positive excess returns. CS_{TVM} strategies earn bigger excess returns than the corresponding TS strategies, and the difference is statistically significant for the 60×1 strategy.

All scaled CS strategies with bonds, except the 3×1 and the 12×1 strategies, and all scaled TS strategies earn significantly positive excess returns. While CS strategies are zero net investment strategies, the net long positions for scaled TS range from \$2.23($=8.33-6.10$) to \$13.38($=14.33-0.95$). For instance, the 12×1 scaled TS strategy has a net long exposure of \$5.42 on average to bond index futures contracts. Bond futures earned positive returns during this sample period, and, hence, a part of the excess returns for the TS strategy is due to this net long position. In contrast, the positive returns for the CS strategies are due to the difference between the returns on the long and short positions.

The scaled CS_{TVM} with bond indices also earns significantly positive returns for all ranking periods. For example, the 12×1 scaled CS_{TVM} strategy earns

Table 12
Portfolio returns based on time-series and cross-sectional strategies for individual asset classes

	Unscaled strategies							Scaled strategies						
Ranking period	TS	CS	CS_{TVM}	TS−CS	TS−CS_{TVM}	$Long	$Short	TS	CS	CS_{TVM}	TS−CS	TS−CS_{TVM}	$Long	$Short
A. Equities														
1	1.47	−3.98	2.65	5.45	−1.17	1.15	−0.85	2.57	−2.88	4.23	5.45	−1.65	1.39	−0.90
	(0.32)	(−1.89)	(0.52)	(1.26)	(−0.70)	(3.90)	(3.90)	(0.56)	(−1.31)	(0.83)	(1.24)	(−0.92)	(7.20)	(2.21)
3	5.26	−3.21	4.37	8.47	0.88	1.23	−0.77	6.64	−3.07	6.19	9.71	0.45	1.53	−0.76
	(1.02)	(−1.36)	(0.70)	(1.83)	(0.44)	(5.79)	(5.79)	(1.30)	(−1.20)	(1.02)	(2.02)	(0.21)	(9.35)	(6.10)
12	13.19	1.85	14.06	11.34	−0.87	1.29	−0.71	17.85	2.30	19.36	15.55	−1.51	1.67	−0.61
	(2.40)	(0.77)	(2.10)	(2.33)	(−0.40)	(6.83)	(6.83)	(3.21)	(0.90)	(2.90)	(2.96)	(−0.63)	(10.83)	(10.63)
60	−6.56	2.57	−5.44	−9.13	−1.12	1.18	−0.82	−4.54	3.08	−3.80	−7.62	−0.74	1.44	−0.88
	(−1.28)	(1.26)	(−0.99)	(−1.88)	(−0.77)	(4.48)	(4.48)	(−0.89)	(1.25)	(−0.69)	(−1.52)	(−0.43)	(8.66)	(2.32)
B. Currencies														
1	5.14	1.80	5.52	3.34	−0.38	1.07	−0.93	11.92	4.60	12.99	7.32	−1.07	2.31	−1.99
	(2.11)	(1.18)	(1.91)	(1.68)	(−0.38)	(1.98)	(1.98)	(2.78)	(1.32)	(2.36)	(1.98)	(−0.45)	(16.84)	(−13.00)
3	7.23	1.51	8.70	5.72	−1.46	1.11	−0.89	14.14	4.63	18.19	9.51	−4.05	2.39	−1.90
	(2.96)	(0.98)	(2.98)	(2.73)	(−1.28)	(3.00)	(3.00)	(3.27)	(1.35)	(3.39)	(2.46)	(−1.64)	(17.60)	(−11.78)
12	4.92	2.35	5.73	2.57	−0.81	1.21	−0.79	13.17	6.30	15.49	6.88	−2.32	2.61	−1.69
	(1.86)	(1.51)	(1.83)	(1.22)	(−0.76)	(5.77)	(5.77)	(2.80)	(1.82)	(2.62)	(1.80)	(−0.92)	(20.59)	(−9.01)
60	0.27	−2.18	−0.70	2.45	0.96	1.28	−0.72	1.31	−4.62	−0.72	5.93	2.04	2.71	−1.63
	(0.10)	(−1.39)	(−0.22)	(1.01)	(0.80)	(7.07)	(7.07)	(0.27)	(−1.27)	(−0.12)	(1.27)	(0.71)	(18.41)	(−7.20)
C. Commodities														
1	9.56	7.33	11.46	2.23	−1.90	1.01	−0.99	7.15	5.99	9.05	1.16	−1.90	0.87	−0.87
	(2.38)	(2.07)	(2.46)	(0.84)	(−1.06)	(0.57)	(0.57)	(2.61)	(2.31)	(2.80)	(0.61)	(−1.35)	(−7.12)	(6.50)
3	13.59	9.91	15.48	3.69	−1.89	1.03	−0.97	11.13	8.37	12.48	2.76	−1.35	0.88	−0.86
	(3.59)	(2.95)	(3.43)	(1.43)	(−1.12)	(1.47)	(1.47)	(4.34)	(3.41)	(3.99)	(1.53)	(−1.02)	(−6.66)	(7.20)
12	13.39	10.94	15.08	2.45	−1.68	1.04	−0.96	12.23	9.63	14.25	2.59	−2.02	0.85	−0.86
	(3.50)	(3.16)	(3.06)	(0.87)	(−0.79)	(1.45)	(1.45)	(4.71)	(3.74)	(4.25)	(1.21)	(−1.23)	(−7.30)	(5.83)
60	3.16	4.63	4.02	−1.47	−0.86	1.12	−0.88	1.77	3.76	3.54	−2.00	−1.77	0.90	−0.83
	(0.83)	(1.26)	(0.88)	(−0.53)	(−0.44)	(5.66)	(5.66)	(0.63)	(1.33)	(1.04)	(−0.92)	(−1.15)	(−4.97)	(7.15)
D. Bonds														
1	3.66	1.52	4.83	2.14	−1.17	1.17	−0.83	15.22	13.45	24.69	1.77	−9.47	8.33	−6.10
	(2.74)	(1.55)	(2.62)	(2.50)	(−1.63)	(4.69)	(4.69)	(3.27)	(2.17)	(2.70)	(0.41)	(−1.81)	(23.10)	(−15.62)
3	2.63	0.65	3.92	1.98	−1.28	1.21	−0.79	12.78	8.28	22.39	4.50	−9.61	8.48	−5.96
	(1.87)	(0.67)	(1.98)	(2.09)	(−1.57)	(5.33)	(5.33)	(2.58)	(1.37)	(2.36)	(1.11)	(−1.77)	(23.24)	(−15.03)
12	4.43	1.13	5.18	3.30	−0.75	1.43	−0.57	18.18	10.04	26.26	8.14	−8.08	9.98	−4.56
	(3.02)	(1.16)	(2.57)	(3.35)	(−0.95)	(11.70)	(11.70)	(3.45)	(1.60)	(2.61)	(1.93)	(−1.42)	(26.44)	(−10.97)
60	5.24	1.85	6.78	3.39	−1.54	1.87	−0.13	21.63	12.62	33.37	9.01	−11.75	14.33	−0.95
	(3.54)	(2.10)	(3.19)	(3.82)	(−2.06)	(57.52)	(57.52)	(3.43)	(2.05)	(2.91)	(2.37)	(−2.04)	(41.19)	(0.34)

We sort assets based on prior returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. The long portfolio under the TS strategy comprises all assets with positive excess returns during the ranking period, and the short portfolio comprises the other assets. The long portfolio under the CS strategy comprises all assets with returns in excess of cross-sectional mean returns during the ranking period, and the short portfolio comprises the other assets. The unscaled strategies form equal-weighted long and short portfolios. The scaled strategies scale portfolio weights based on past realized volatility of each asset (please see text for details). Portfolios are held for 1 month. The table reports the annualized excess returns for the long minus short portfolios. The CS_{TVM} strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (please refer to text for details). $Long and $Short are the average dollar positions of the TS strategy. Numbers in parentheses are the corresponding t-statistics (t-statistics for $Long and $Short are calculated for the null of $1 and −$1, respectively). The four asset classes are equities, currencies, commodities, and bonds. The sample period is from 1985 to 2013.

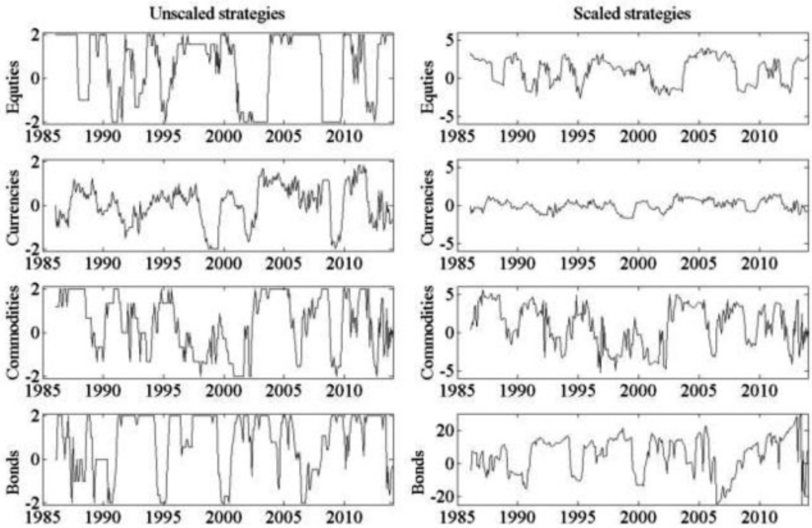

Figure 5
Net long positions for sorts based on time-series 12 $\times$ 1 strategies for individual asset classes
We sort asset classes based on prior returns during a ranking period of 12 months following the time-series strategy, where the long portfolio comprises all assets with positive excess returns during the ranking period, and the short portfolio comprises the other assets. The unscaled strategies form equal-weighted long and short portfolios. The scaled strategies scale portfolio weights based on past realized volatility of each asset (see text for details). Portfolios are kept for a holding period of 1 month. The figure shows the net long position (in dollars) for these strategies for different asset classes (the scale changes for the y-axis in the right-hand-side plots and in the bottom-right plot). The sample period is from 1985 to 2013.

26.26%. In comparison, the 12 $\times$ 1 scaled TS strategy earns a smaller return of 18.18%; the difference of 8.08% is not statistically significant though. The other scaled TS strategies also earn smaller returns than scaled CS_{TVM} strategies.

Overall, TS strategies earn bigger returns than corresponding CS strategies in most cases but the return differences are statistically significant in only a few instances. The net long positions for the TS strategies are all positive except for the scaled TS strategies for currencies. Figure 5 presents the net long positions for the 12 $\times$ 1 strategy for the individual asset classes. The net long positions in the right-hand-side panels for scaled strategies are all bigger than the corresponding left-hand-side panels for unscaled strategies. Particularly noteworthy are the net long positions for scaled bond strategies in the bottom right-hand corner.

All asset classes on average earn positive returns during the sample period and, hence, the net long positions of the TS strategies contribute to their bigger returns relative to CS strategies that are net-zero investments. The CS_{TVM} strategies which have identical net long investments as the TS strategies earn about the same returns as the latter, except in the case of bonds where the strategies earn significantly bigger returns. We find similar results with alphas as well.

6. Sources of TVM Excess Returns: International Asset Classes

Table 13 presents the decomposition of the time-varying investment in the market for all asset classes, as well as for individual asset classes. For all asset classes, the risk premium component is significant at all horizons. However, the market timing component is insignificant. Therefore, the size of the net long position does not predict the future returns of the asset class index.

For individual asset classes, the risk premium component is significant for bonds and marginally significant for equities, but insignificant for currencies and commodities, reflecting bigger net long position for bonds than that for other asset classes. On the other hand, as discussed earlier in Section 4, the market timing component reflects the autocorrelation of an equal-weighted index return. The market timing component is significant for currencies and commodities for all ranking periods except the 60-month period. For equities, this component is significantly positive for the 12-month ranking period, but significantly negative for the 60-month ranking period. For bonds, the TVM return for scaled strategies is much bigger than that for unscaled strategies due to bigger net long positions as discussed in the previous section. At the same time, the market timing component for bonds is significant only at short horizons. These results indicate that a significant part of returns to TS strategies within individual asset classes is due to the ability of the net long positions to predict future asset class returns rather than the ability of TS strategies to identify individual assets that underperform or outperform asset class average.

We also examine whether the profitability of TVM with international asset classes is related to the variables that we previously used in Section 4. We report the results in Internet Appendix Table A2.2, where we find that none of these variables is related to TVM returns. Therefore, as with individual stocks, the profitability of TVM for asset classes is not related to factors that predict market risk premium.

7. Results in Perspective

This section discusses the economic implications of our findings for asset pricing models and for understanding the relative performances of TS and CS phenomena documented in the literature.

7.1 Misspecified tests and mistaken inferences

Our findings have important implications for the design of reliable empirical tests. For example, MOP's (2012) method of using cross-strategy intercepts in judging whether TS or CS is the dominant strategy misses an important economic dimension. Since the TS strategy is a positive net investment strategy on average, the positive intercept in the regression of TS excess returns against CS excess returns reflects the risk component inherent in the TS strategy, and it does not necessarily have any implications for whether one strategy fully captures the other.

Table 13
Decomposition of time-varying investment in the market for asset classes

	Unscaled strategies					Scaled strategies				
Ranking period	TVM	Risk premium	Market timing	$Net long	Equal-weighed return	TVM	Risk premium	Market timing	$Net long	Inverse volatility-weighted return
A. All asset classes										
1	0.97	0.85	0.12	0.15	5.51	1.15	2.00	−0.85	0.62	3.20
	(0.97)	(2.88)	(0.12)	(4.75)	(3.73)	(0.82)	(3.45)	(−0.68)	(4.55)	(5.25)
3	2.53	1.24	1.29	0.23	5.45	2.35	2.51	−0.16	0.79	3.17
	(2.56)	(3.20)	(1.28)	(7.49)	(3.71)	(1.76)	(3.98)	(−0.14)	(5.99)	(5.38)
12	2.74	2.01	0.73	0.38	5.30	4.58	4.79	−0.21	1.56	3.08
	(2.48)	(3.32)	(0.75)	(11.58)	(3.52)	(3.08)	(4.70)	(−0.19)	(11.79)	(5.12)
60	1.79	2.86	−1.06	0.63	4.56	7.26	7.67	−0.41	3.21	2.39
	(1.26)	(2.77)	(−1.30)	(23.18)	(2.76)	(4.02)	(3.89)	(−0.49)	(33.40)	(3.91)
B. Equities										
1	6.62	1.87	4.75	0.30	6.13	7.11	3.00	4.10	0.49	6.18
	(1.53)	(1.73)	(1.07)	(3.90)	(2.04)	(1.65)	(1.92)	(0.91)	(5.31)	(2.13)
3	7.58	2.86	4.72	0.46	6.16	9.25	4.86	4.39	0.78	6.23
	(1.51)	(1.87)	(0.92)	(5.79)	(2.04)	(1.86)	(2.03)	(0.88)	(8.50)	(2.13)
12	12.21	3.34	8.87	0.58	5.78	17.06	6.22	10.84	1.06	5.86
	(2.27)	(1.74)	(1.62)	(6.83)	(1.86)	(3.11)	(1.88)	(2.02)	(11.20)	(1.96)
60	−8.01	1.54	−9.55	0.37	4.19	−6.88	2.41	−9.29	0.56	4.30
C. Currencies										
1	3.72	0.44	3.28	0.14	3.22	8.39	0.90	7.49	0.32	2.77
	(1.82)	(1.30)	(1.62)	(1.98)	(2.08)	(2.32)	(1.34)	(2.09)	(2.21)	(2.01)
3	7.19	0.67	6.52	0.21	3.13	13.56	1.32	12.24	0.49	2.72
	(3.49)	(1.52)	(3.26)	(3.00)	(2.05)	(3.83)	(1.54)	(3.57)	(3.27)	(2.00)
12	3.38	1.09	2.29	0.41	2.64	9.20	2.22	6.98	0.92	2.41
	(1.52)	(1.60)	(1.10)	(5.77)	(1.72)	(2.36)	(1.62)	(1.93)	(6.21)	(1.75)
60	1.48	1.09	0.39	0.56	1.95	3.90	1.86	2.04	1.08	1.73
	(0.64)	(1.18)	(0.19)	(7.07)	(1.21)	(0.95)	(1.15)	(0.54)	(6.23)	(1.19)
D. Commodities										
1	4.13	0.16	3.96	0.02	6.97	3.06	−0.02	3.08	0.00	5.81
	(1.77)	(0.51)	(1.69)	(0.57)	(2.77)	(1.97)	(−0.09)	(2.01)	(−0.09)	(2.61)
3	5.58	0.43	5.15	0.06	6.90	4.11	0.11	4.00	0.02	5.74
	(2.29)	(1.17)	(2.07)	(1.47)	(2.74)	(2.59)	(0.49)	(2.53)	(0.56)	(2.58)
12	4.13	0.49	3.64	0.07	6.96	4.62	−0.06	4.67	−0.01	5.85
	(1.56)	(1.18)	(1.40)	(1.45)	(2.70)	(2.63)	(−0.23)	(2.68)	(−0.25)	(2.58)
60	−0.61	1.49	−2.10	0.24	6.31	−0.22	0.38	−0.61	0.07	5.32
	(−0.26)	(2.11)	(−1.03)	(5.66)	(2.25)	(−0.13)	(1.33)	(−0.39)	(1.86)	(2.12)
E. Bonds										
1	3.31	1.07	2.24	0.34	3.11	11.24	4.12	7.11	2.23	1.85
	(2.86)	(2.74)	(2.06)	(4.69)	(3.73)	(2.49)	(2.57)	(1.69)	(3.76)	(3.91)
3	3.26	1.31	1.95	0.41	3.16	14.11	4.79	9.32	2.52	1.90
	(2.68)	(2.94)	(1.76)	(5.33)	(3.80)	(3.05)	(2.74)	(2.18)	(4.19)	(4.02)
12	4.05	2.56	1.49	0.85	3.00	16.22	10.40	5.82	5.42	1.92
	(3.11)	(3.35)	(1.46)	(11.70)	(3.58)	(3.21)	(3.55)	(1.33)	(8.86)	(4.00)
60	4.93	5.11	−0.18	1.74	2.93	20.75	25.23	−4.48	13.38	1.89
	(3.50)	(3.54)	(−0.29)	(57.52)	(3.54)	(3.35)	(3.90)	(−1.13)	(32.48)	(3.89)

This table reports the decomposition of the time-varying investment in the market (TVM) into the two components related to risk premium and market timing (please refer to text for details). We form portfolios using time-series (TS) strategies, where the long portfolio comprises all assets with positive excess returns during the ranking period, and the short portfolio comprises the other assets. The unscaled strategies form equal-weighted long and short portfolios. The scaled strategies scale portfolio weights based on past realized volatility of each asset (please see text for details). The table reports the decomposition of the time-varying investment in the market (TVM) into the two components related to risk premium and market timing (please refer to text for details). $Net long is the average net long position (in dollars) of the time-series strategy, Equal-weighted return and inverse volatility-weighted return are the average annualized holding period return on equal-weighted and inverse volatility-weighed return indexes of all assets included in the portfolio sorts. Numbers in parentheses are the corresponding t-statistics. The sample period is from 1985 to 2013.

Our comparison of TS with CS_{TVM} directly adjusts for differences due to TS strategies' investment in risky assets by taking an identical net long position in the market, and we also focus on risk-adjusted returns. Our findings indicate that the TS strategies do not subsume CS strategies for individual stocks after adjusting for risk differences due to the time-varying net long investment in risky assets. Although it is well-known that comparisons of different strategies should appropriately adjust for differences in risk to draw reliable inferences, the inherent risk differences are not always apparent and, hence, may be overlooked in the case of cross-strategy regressions.

MOP (2012) also examine strategies using portfolio weights proportional to past returns as LM (1990) propose to identify "what features are common and unique to the two strategies."[13] To understand what we can learn from such comparisons, we follow MOP and construct TS and CS strategies using LM weights as follows

$$w^{CS}_{it-1,LM} = \frac{1}{N_{t-1}}\left(R_{it-1} - \bar{R}_{t-1}\right) \text{ and } w^{TS}_{it-1,LM} = \frac{1}{N_{t-1}} R_{it-1}, \tag{11}$$

where N_{t-1} is the number of stocks in the sample, and R_{it-1} and $\bar{R}_{t-1}$ are the returns on stock i and the equal-weighted index.

Here again the CS strategies, by construction, take zero-net long positions each month, but TS strategies take time-varying net long positions. We compute the net long positions for the TS strategy each month and invest that amount in the equal-weighted index to construct CS_{TVM} portfolios.

Table 14 presents portfolio returns for the strategies with LM (1990) portfolio weights. The returns to CS strategies are negative for 1-, 36-, and 60-month horizons and positive for 3-, 6-, and 12-month horizons consistent with short- and long-term reversal and medium-term momentum. In contrast, the results indicate that all TS strategies earn positive excess returns, which seems like an entirely different phenomenon. Interestingly, the returns to CS_{TVM} are *identical* to those of TS. Why do the strategies with LM-weights show zero difference between TS and CS_{TVM}?

We can see from Equation (11) that $w^{TS}_{it-1,LM} - w^{CS}_{it-1,LM} = \bar{R}_{t-1} / N_{t-1}$. Thus, the weights on individual stocks differ only by a constant for the TS and the CS strategies. In other words, TS strategies differ from corresponding strategies by exactly TVM. We can also calculate the difference in return on these two strategies as

$$R^{TS}_{t,LM} - R^{CS}_{t,LM} = \sum\nolimits_i \Delta w_{it-1,LM} R_{it} = \text{NetLong}_t \times \bar{R}_t = R^{TVM}_{t,LM}. \tag{12}$$

Equation (12) shows that LM (1990) type TS strategy is mathematically equal to the corresponding CS strategy plus a time-varying investment in the equal-weighted market index (TVM).

13 Conrad and Kaul (1998) and Lewellen (2002) also examine the performance of CS strategies with individual stocks using LM (1990) weights.

Table 14
Time-series and cross-sectional strategies with Lo and MacKinlay (1990) portfolio weights

	Holding period = Ranking period				Holding period = 1 month			
Ranking period	TS	CS	CS_{TVM}	\$Net long	TS	CS	CS_{TVM}	\$Net long
1	0.27	−0.29	0.27	0.01	0.27	−0.29	0.27	0.01
	(1.40)	(−2.51)	(1.40)	(7.20)	(1.40)	(−2.51)	(1.40)	(7.20)
3	0.43	0.10	0.43	0.04	0.58	−0.05	0.58	0.04
	(1.16)	(0.41)	(1.16)	(13.19)	(1.30)	(−0.16)	(1.30)	(11.32)
6	0.99	0.58	0.99	0.08	1.02	0.19	1.02	0.08
	(1.65)	(1.48)	(1.65)	(18.65)	(1.42)	(0.36)	(1.42)	(15.33)
12	0.73	0.03	0.73	0.17	2.39	1.05	2.39	0.18
	(0.79)	(0.06)	(0.79)	(27.64)	(2.09)	(1.33)	(2.09)	(21.52)
36	2.72	−1.83	2.72	0.62	2.77	−0.82	2.77	0.60
	(1.42)	(−2.61)	(1.42)	(52.19)	(1.30)	(−0.77)	(1.30)	(38.50)
60	7.99	−2.76	7.99	1.20	6.27	−1.31	6.27	1.17
	(2.42)	(−2.52)	(2.42)	(68.69)	(1.65)	(−0.71)	(1.65)	(43.09)

We form portfolios based on returns during a ranking period ranging from 1 to 60 months following either the time-series (TS) strategy or the cross-sectional (CS) strategy. TS strategies form portfolios by weighting each asset in proportion to its excess returns during various ranking periods. CS strategies form portfolios by weighting each asset in proportion to the difference between its return and the return of an equal weighted portfolio of all assets during various ranking periods. The CS_{TVM} strategy is constructed as the sum of CS strategy and the time-varying investment (TVM) in the market (please refer to text for details). Portfolios are kept for a holding period equal to ranking period or equal to 1 month. We use overlapping portfolios, like in Jegadeesh and Titman (1993), for holding periods greater than 1 month. The table reports annualized returns. \$Net long is average net long position (in dollars) of the time-series strategy. Numbers in parentheses are the corresponding t-statistics. A stock is defined as non-micro-cap if it is above the 20th percentile of NYSE market capitalization. The sample period is from 1946 to 2013.

Therefore, the differences between these strategies are entirely due to the time-series behavior of equal-weighted index returns; we cannot learn anything about the behavior of individual stock returns from the differences in these two strategies. In particular, we cannot learn whether one strategy is better than the other at picking relative winners and losers among individual assets using the LM (1990) approach. MOP (2012) mistakenly conclude, “Since the cross-sectional correlation of lead-lag effects among assets contributes negatively to XSMOM, it is not surprising that TSMOM, which does not depend on the cross-serial correlations across assets, produces higher profits than XSMOM.”

There are also several suggestions in the literature that TS and CS strategies perform differently because one uses an individual asset’s past returns as the threshold for taking long or short positions, while the other uses returns relative to other assets. For example, Bunn and Shiller (2014) screen sectors based on their own past returns and claim that their strategy is very close to MOP (2012) rather than to the commonly used CS strategy because their approach uses “the momentum of an individual asset to determine its impact on this specific asset’s future returns.” Empirically, we show that the TS strategy performs differently than the CS strategy only because of its time-varying net long investments in the market index, but Bunn and Shiller’s screening approach does not result in any net long positions. Therefore, in an economic sense, their approach is closer to CS strategies than TS strategies because the screening thresholds for categorizing past winners and losers per se do not really matter.

7.2 Time-series asset pricing factor

Currently, researchers most often use the CS momentum factor (UMD) introduced by Carhart (1997) to control for momentum. One of MOP's (2012) suggestions is that TSMOM is a useful factor to consider for inclusion in a multifactor asset pricing model, a suggestion that some researchers follow. For instance, Koijen et al. (Forthcoming) use the TSMOM factor to evaluate the performance of carry-based strategies.

Would TSMOM be incrementally useful in a multifactor asset pricing model? For individual stocks, TSMOM is equivalent to the sum of a CS factor and a time-varying investment in the market TVM. Therefore, the usefulness of the TSMOM factor depends on whether there are specific advantages for such a composite factor. The market factor already captures market risk, and, hence, the addition of an equal-weighted index factor through TSMOM is likely redundant. Regarding the market timing, it is not entirely clear when this component would serve as an incrementally useful benchmark. Recall that the market timing component is driven by past market returns. Therefore, if one were interested in controlling for the market timing implicit in TSMOM, it may be better to use past market returns directly (e.g., squared market returns proposed by Merton and Henriksson 1981) as a separate factor rather than as a part of a factor meant to capture momentum. Leaving these market components aside, TS and CS strategies earn about equal returns for individual stocks, but the scaled TS factor performs worse than do the corresponding CS strategies with international asset classes. Therefore, factors based on the TS approach are unlikely to be incrementally useful in multifactor asset pricing models that already include factors based on the CS approach.

7.3 Implications for behavioral theories

MOP (2012) argue that the predictions of behavioral models, such as those in Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999), have "direct implications for time series, rather than cross-sectional, predictability" because they all focus on a single risky asset. This claim seems to have some merit on the surface, but a closer look at the sources of TS excess returns indicate that this claim may not be entirely accurate. To see this point, consider Barberis, Shleifer, and Vishny. Their model has a single risky asset whose earnings follow a random walk. However, investors mistakenly assume that the earnings either follow a mean reverting process or trending process and as a result the asset's price is sometimes overvalued and sometimes undervalued, which leads to return predictability.

Since TS strategies consider one stock at a time, it appears that this strategy profits entirely by picking undervalued and overvalued stocks. However, TS strategies earn excess returns not only from any overvaluation or undervaluation of individual stocks, but also from its time-varying investments in the aggregate market. As Table 7 shows, TVM's profits are due to risk premium as well as due to market timing. As we discussed earlier, the market timing component of TVM arise from the serial correlation of aggregate market returns, and it is not a property of individual stock returns. There are two sources of profits for TS strategies, but the behavioral models do not incorporate the market timing component in the TVM. Therefore, the relation between the TS and the behavioral models in the literature are not as direct as what may appear on the surface.

The CS approach is perhaps more suitable to test the implication of the behavioral models than the TS approach. To see this point heuristically, suppose stock returns follow the market model below

$$R_{it}=\alpha_i+R_{mt}+e_{it}, \tag{13}$$

where we assume that beta is equal to one for all stocks. Because R_{mt} is common across stocks, cross-sectional ranks based on past returns would depend primarily on e_{it}, the firm-specific component of returns.[14] Since return predictability in behavioral models is due to asset specific overvaluation or undervaluation, it would be more appropriate to test their implications based on a CS approach. To the extent that betas are different across stocks in practice, the CS approach may not exactly represent the behavioral models, but it is, nevertheless, closer than the TS approach, which takes long or short positions based on both R_{mt} and e_{it}.

8. Conclusions

The literature on return predictability based on past returns typically uses cross-sectional ranks (or a CS approach) to form predictive portfolios. MOP (2012) propose a time-series (TS) approach that takes long or short positions in an asset by only looking back at its own past returns. MOP use a sample of international asset classes and report that portfolios formed based on the TS approach are significantly more profitable than those based on the CS approach.

We first examine TS and CS strategies with U.S. stocks. We find striking differences in the excess returns earned by these strategies, which is similar to what MOP (2012) report for asset classes. When we take a closer look, we find that a key difference between these approaches is that the net active investments in risky assets made by CS strategies equal zero, but TS strategies make net long investments. We find that the excess returns of CS and TS strategies are generally about equal after adjusting for the net long positions of the TS strategies. The only substantive difference we find is that the TS approach misses the short horizon return reversals that Jegadeesh (1990) documents using the CS approach.

14 Cross-sectional ranks based on past returns also depend on differences in α_i, which is the unconditional expected return. However, Jegadeesh and Titman (1995) empirically show that very little, if any, of the return predictability is due to differences in unconditional expected returns.

We also compare the performances of TS and CS strategies with a sample of international asset classes with inverse volatility scaling like in MOP (2012). MOP compare scaled TS strategies with equal-weighted CS strategies to reach the conclusion that TS strategies subsume CS strategies. However, the performance of scaled TS strategies are not directly comparable with equal-weighted CS strategies because the scaled TS strategies take on significantly bigger active positions in risky assets than equal-weighted CS strategies, and unlike CS strategies, the scaled TS strategies have significantly positive net long positions. For example, a scaled TS strategy based on a 12-month ranking period is on average \$3.28 long and \$1.73 short, and the equal-weighted CS strategy is \$1 long and \$1 short.

When we compare the scaled TS strategies with similarly scaled CS strategies, we find that the TS strategies perform significantly worse than the CS strategies. The scaled CS strategies outperform scaled TS strategies partly because of the differences in the asset class compositions of TS and CS portfolios. Additionally, CS strategies exhibit a better ability to identify overvalued and undervalued bonds.

Appendix: Standard Error Calculation for the Decomposition of TVM Return

For any two random variables X and Y, define $d_{XY}=E\left[(X-\mu_X)^2(Y-\mu_Y)^2\right]$. Then it can be shown that

$$var\left(\bar{X}\cdot\bar{Y}\right)=\frac{1}{T}\left(\sigma_X^2\mu_Y^2+\sigma_Y^2\mu_X^2+2\mu_X\mu_Y\sigma_{XY}\right)+\frac{1}{T^2}\left(\sigma_X^2\sigma_Y^2+\sigma_{XY}^2\right) \tag{A1}$$

$$var[S_{XY}]=\frac{1}{T}\left[d_{XY}+\frac{1}{T-1}\sigma_X^2\sigma_Y^2-\frac{T-2}{T-1}\sigma_{XY}^2\right], \tag{A2}$$

where S_{XY} is the sample covariance between X and Y. Defining $X_t=\text{NetLong}_t$ and $Y_t=\bar{R}_t$ gives us the variance of the risk premium and market timing component from the first and second rows of the above equation, respectively.

References

Amihud, Y. 2002. Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5:31–56.

Asness, C., T. Moskowitz, and L. Pedersen. 2013. Value and momentum everywhere. *Journal of Finance* 68: 929–85.

Barberis, N., A. Shleifer, and R. Vishny. 1998. A model of investor sentiment. *Journal of Financial Economics* 49:307–43.

Barroso, P., and P. Santa-Clara. 2015. Momentum has its moments. *Journal of Financial Economics* 116:111–20.

Blume, M., and R. Stambaugh. 1983. Biases in computed returns: An application to the size effect. *Journal of Financial Economics* 12:387–404.

Bunn, O., and R. Shiller. 2014. Changing times, changing values: A historical analysis of sectors within the U.S. stock market 1872-2013. Working Paper, NBER.

Carhart, M. 1997. On persistence in mutual fund performance. *Journal of Finance* 52:57–82.

Chan, K., A. Hameed, and W. Tong. 2000. Profitability of momentum strategies in the international equity markets. *Journal of Financial and Quantitative Analysis* 35:153–72.

Conrad, J., and G. Kaul. 1998. An anatomy of trading strategies. *Review of Financial Studies* 11:489–519.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor psychology and security market under- and overreactions. *Journal of Finance* 53:1839–85.

De Bondt, W., and R. Thaler. 1985. Does the stock market overreact? *Journal of Finance* 40:793–805.

Fama, E., and K. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33:3–56.

He, X.-Z., and K. Li. 2015. Profitability of time series momentum. *Journal of Banking and Finance* 53:140–57.

Hong, H., and J. Stein. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54:2143–84.

Jegadeesh, N. 1990. Evidence of predictable behavior of security returns. *Journal of Finance* 45:881–98.

Jegadeesh, N., and S. Titman. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48:65–92.

————. 1995. Overreaction, delayed reaction, and contrarian profits. *Review of Financial Studies* 8:973–93.

Kim, A., Y. Tse, and J. Wald. 2016. Time series momentum and volatility scaling. *Journal of Financial Markets* 30:103–24.

Koijen, R., T. Moskowitz, L. Pedersen, and E. Vrugt. Forthcoming. Carry. *Journal of Financial Economics*.

Lewellen, J. 2002. Momentum and autocorrelation in stock returns. *Review of Financial Studies* 15:533–63.

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

Lyon, J., B. Barber, and C.-L. Tsai. 1999. Improved methods for tests of long-run abnormal stock returns. *Journal of Finance* 54:165–201.

Menkhoff, L., L. Sarno, M. Schmelling, and A. Schrimpf. 2012. Currency momentum strategies. *Journal of Financial Economics* 106:660–84.

Merton, R., and R. Henriksson. 1981. On market timing and investment performance. II. Statistical procedures for evaluating forecasting skill. *Journal of Business* 54:513–33.

Moreira, A., and T. Muir. 2017. Volatility managed portfolios. *Journal of Finance* 72:1611–44.

Moskowitz, T., Y. Ooi, and L. Pedersen. 2012. Time series momentum. *Journal of Financial Economics* 104:228–50.

Novy-Marx, R., and M. Velikov. 2016. A taxonomy of anomalies and their trading costs. *Review of Financial Studies* 29:104–47.

Rapach, D., and G. Zhou. 2013. Forecasting stock returns. In *Handbook of economic forecasting*. Eds. G. Elliot, C. W. J. Granger, and A. Timmerman, volume 2A, 329–83. Amsterdam: Elsevier.