Time Series Momentum

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Abstract

We document significant "time series momentum" in equity index, currency, commodity, and bond futures for *each* of the 58 liquid instruments we consider. We find persistence in returns for 1 to 12 months that partially reverses over longer horizons, consistent with sentiment theories of initial under-reaction and delayed over-reaction. A diversified portfolio of time series momentum strategies across all asset classes delivers substantial abnormal returns with little exposure to standard asset pricing factors, and performs best during extreme markets. We show that the returns to time series momentum are closely linked to the trading activities of speculators and hedgers, where speculators appear to profit from it at the expense of hedgers.

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1. Introduction: A Trending Walk Down Wall Street

We document an asset pricing anomaly we term "time series momentum," which is remarkably consistent across very different asset classes and markets. Specifically, we find strong positive predictability from a security's own past returns for a large set (almost five dozen) of diverse futures and forward contracts that include country equity indices, currencies, commodities, and sovereign bonds over more than 25 years of data. We find that the past 12 month excess return of each instrument is a positive predictor of its future return. This time series momentum or "trend" effect persists for about a year and then partially reverses over longer horizons. These findings are robust across a number of sub-samples, look-back periods, and holding periods. In fact, 12-month time series momentum profits are positive not just on average across these assets, but for *every* asset contract we examine (58 in total).

Time series momentum is related to, but different from, the phenomenon known as "momentum" in the literature, which is cross-sectional in nature. The momentum literature focuses on the *relative* performance of securities in the *cross-section*, finding that securities that recently outperformed their peers (over the past 3 to 12 months) continue to outperform their peers on average over the next month (up to a year).[2] Rather than focusing on the relative returns of securities in the cross-section, time series momentum focuses purely on a security's *own* past return.

We argue time series momentum directly matches the predictions of many prominent behavioral and rational asset pricing theories. Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) all focus on a single risky asset and therefore have direct implications for time series predictability of the asset's own returns. Likewise, rational theories of momentum (Berk, Green, and Naik (1999), Johnson (2002), Ahn, Conrad, and Dittmar (2003), Zhang (2004), and Sagi and Seasholes (2007)) pertain to a single risky asset.

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[2] Cross-sectional momentum has been documented in U.S. equities (Jegadeesh and Titman (1993), Asness (1994)), other equity markets (Rouwenhorst (1998)), industries (Moskowitz and Grinblatt (1999)), equity indices (Asness, Liew, and Stevens (1997), Bhojraj and Swaminathan (2006)), currencies (Shleifer and Summers (1990)), commodities (Erb and Harvey (2006), Gorton, Hayashi, and Rouwenhorst (2008)), and global bond futures (Asness, Moskowitz, and Pedersen (2009)).

Our finding of positive trends that partially reverse over the long-term may be consistent with initial under-reaction and delayed over-reaction, which theories of sentiment suggest can produce these return patterns.[3] However, our results may also pose several challenges to these theories. First, we find that the correlations of time series momentum strategies across asset classes are larger than the correlations of the asset classes themselves. This suggests a stronger common component to time series momentum across different assets than is present among the assets themselves. Such a correlation structure is not addressed by existing behavioral models. Second, very different types of investors in different asset markets are producing the same patterns at the same time. Third, attempting to link time series momentum to measures of sentiment used in the literature (Baker and Wurgler (2006), Welch (2009)), we fail to find a significant relationship.

To understand the relationship between time series and cross-sectional momentum, their underlying drivers, and relation to theory, we decompose the returns to each following the framework of Lo and MacKinlay (1990) and Lewellen (2002). This allows us to identify the properties of returns that contribute to these patterns, and how they are common and unique to both strategies. We find that positive auto-covariance in our futures contracts' returns drives most of the time series and cross-sectional momentum effects we find in the data. The contribution of the other two return components—serial cross-correlations and variation in mean returns—is small. First, negative serial cross-correlations (i.e., lead-lag effects across securities), which affect cross-sectional momentum but not time series momentum, are negligible and of the "wrong" sign among our instruments. Second, the contribution from mean returns of the assets is also small. Our finding that time series and cross-sectional momentum profits arise due to auto-covariance is consistent with the theories mentioned above. However, they differ from Lewellen's (2002) finding for individual equity returns that temporal

[3] Underreaction can result from the slow diffusion of news (Hong and Stein (1999)), conservativeness and anchoring biases (Barberis, Shleifer, and Vishny (1998), Edwards (1968)), or the disposition effect to sell winners too early and ride losers too long (Shefrin and Statman (1985), Frazzini (2006)). Over-reaction can be caused by positive feedback trading (De Long, Shleifer, Summers, and Waldmann (1990), Hong and Stein (1999)), over-confidence and self-attribution confirmation biases (Daniel, Hirshleifer, and Subrahmanyam (1998)), the representativeness heuristic (Barberis, Shleifer, and Vishny (1998), Tversky and Kahneman (1974)), herding (Bikhchandani, Hirshleifer, and Welch (1992)), or general sentiment (Baker and Wurgler (2006, 2007)).

lead-lag effects, rather than auto-covariances, appear to be the most significant contributor to cross-sectional momentum; Chen and Hong (2002) provide a different interpretation and decomposition consistent with auto-covariance being the primary driver of stock momentum. If results differ across asset classes, understanding why some asset classes might experience more or less time series and cross-sectional momentum from different sources, and what theories might make such predictions, could help identify which factors (behavioral or risk) are key to explaining these patterns. Current theories, risk-based and behavioral, do not make different predictions for different asset classes.

Finally, to better understand what might be driving time series momentum, we examine the trading activity of speculators and hedgers around these return patterns using weekly position data from the Commodity Futures Trading Commission (CFTC). We find that speculators trade with time series momentum, being positioned on average to take advantage of the positive trend in returns for the first 12 months and taking the opposite positions at exactly the time when the trend reverses. Consequently, speculators appear to be profiting from time series momentum at the expense of hedgers. Using a vector auto-regression (VAR), we find that speculators trade in the same direction as a return shock and reduce their positions as the shock dissipates, whereas hedgers take the opposite side of these trades.

In addition, we decompose time series momentum into the component coming from spot price predictability versus the "roll yield" stemming from the shape of the futures curve. While spot price changes are mostly driven by information shocks, the roll yield can be driven by liquidity and price pressure effects in futures markets that affect the return to holding futures without necessarily changing the spot price level. Hence, this decomposition may be a way to distinguish the effects of information dissemination from hedging pressure. We find that both of these effects contribute to time series momentum, but only spot price changes are associated with long-term reversals, consistent with the idea that hedging pressure is more long-lived and not driven by over-reaction.

Our finding of time series momentum in virtually every instrument we examine seems to challenge the notion of market efficiency. In its most basic form, the efficient markets hypothesis implies that knowing whether a price went up or down in the past should not be informative about whether it will go up or down in the future. Our finding of time series momentum is a clear violation of this "random walk" hypothesis. While rejection of the random walk hypothesis does not necessarily imply a rejection of a more sophisticated notion of market efficiency with time-varying risk premia, we further show that a diversified portfolio of time series momentum across all assets is remarkably stable and robust, yielding a high Sharpe ratio with little correlation to passive benchmarks in each asset class or a host of standard asset pricing factors, including cross-sectional momentum. The abnormal returns to time series momentum also do not appear to be compensation for crash risk or tail events. Rather, their returns appear to be largest when the stock market's returns are most extreme—performing best when the market experiences large up and down moves. Hence, time series momentum may be a hedge for extreme events, making its large return premium even more puzzling from a risk-based perspective. The robustness of time series momentum for very different asset classes and markets, the relatively short duration of the predictability (less than a year), and the magnitude of the return premium present significant challenges to the efficient market hypothesis more generally than the random-walk hypothesis.

Our study relates to the literature on return autocorrelation that also tests deviations from the random walk hypothesis, but with some key differences. First, with the notable exception of Cutler, Poterba and Summers (1991) who study a variety of assets including housing and collectibles, the autocorrelation literature pertains almost exclusively to individual equity portfolios in the U.S., finding positive return autocorrelation at daily, weekly, and monthly horizons and negative autocorrelation at annual and multi-year frequencies (Fama and French (1988), Lo and MacKinlay (1988)). We examine a host of different asset classes globally. Second, by definition, studies of autocorrelation examine return predictability where the length of the "look-back period" is the same as the "holding period" over which returns are predicted. This restriction masks significant predictability that is uncovered once look-back periods are allowed to differ from predicted or holding periods. In particular, our result that the past *12 months* of returns strongly predicts returns over the next *1 month* is missed by looking at one year autocorrelations. Third, a significant component of the higher frequency findings in equities are contaminated by micro-structure effects such as stale prices (Richardson

(1993), Ahn, Boudoukh, Richardson, and Whitelaw (2002)). Focusing on liquid futures instead of individual stocks and looking at lower frequency data (one year) mitigates many of these issues. Finally, while this literature focuses on prices, we link time series predictability to the dynamics of hedger- and speculator positions.

Our paper is also related to the literature on futures return premia (Bodie and Rosansky (1980), Fama and French (1987), Hodrick and Srivastava (1987), Bilson (1981), Rzepczynski (1987), Goldenberg (1988), Bessembinder (1992), and de Roon, Nijman, and Veld (2000)). However, our time series momentum strategies are both long and short and have a small average passive exposure to the major asset classes and hence to unconditional return premia, and focus on a much shorter horizon than the multi-year patterns documented in these other studies.

The rest of the paper is organized as follows. Section 2 describes our data on futures returns and the positioning of hedgers and speculators. Section 3 documents time series momentum at the one year horizon and reversals beyond one year. We also examine the correlation of time series momentum strategies within and across asset classes, their relation to other known return factors, and their performance during extreme markets, relating our findings to rational risk-based and behavioral asset pricing models. Section 4 examines the relation between time series and cross-sectional momentum. Section 5 studies the evolution of time series momentum and its relation to investor speculative and hedging positions. Section 6 concludes.

2. Data and Preliminaries

We describe briefly the various data sources we use in our analysis.

A. Futures returns

Our price data consists of futures prices for 24 commodity futures, 12 cross-currency pairs (with 9 underlying currencies), 9 developed equity indices, and 13 developed government bond futures, from January 1965 through December 2009. We provide details on each instrument and their data sources, which mainly come from Datastream, Bloomberg, and various exchanges, in Appendix A.

We construct a return series for each instrument as follows. Each day, we compute the daily excess return of the most liquid futures contract (typically the nearest or next nearest to delivery contract), and then compound the daily returns to a total return index from which we can compute returns at any horizon. Bessembinder (1992) and de Roon, Nijman, and Veld (2000) compute returns on futures contracts similarly. For the equity indices, our return series are almost perfectly correlated with the corresponding returns in excess of the Treasury bill rate of the underlying cash indices. Bessembinder (1992) and de Roon, Nijman, and Veld (2000) similarly find that futures returns are highly correlated with spot returns on the same underlying asset.

Table 1 presents summary statistics of the returns on our futures contracts. The first column shows when our data starts, while the next two columns report the time series mean and standard deviation (annualized) of each contract by asset class: commodities, equity indices, bonds, and currencies. As Table 1 highlights, there is significant variation in sample mean returns across the different contracts. Equity index, bonds, and currencies yield predominantly positive excess returns, while various commodity contracts yield positive, zero, and even negative excess average returns over the sample period. Only the equity and bond futures exhibit statistically significant and consistent positive excess average returns.

More striking are the differences in volatilities across the contracts. Not surprisingly, commodities and equities have much larger volatilities than bond futures or currency forward contracts. But, even among the commodities, there is substantial cross-sectional variation in volatilities. One issue is how to make comparisons across instruments or how to combine various instruments into a diversified portfolio when they have vastly different volatilities. For example, the volatility of natural gas futures is about 50 times larger than that of 2-year US bond futures. We discuss below how we deal with this issue in our analysis.

B. Trading positions

We also use data on the positions of speculators and hedgers from the Commodity Futures Trading Commission (CFTC) as detailed in Appendix A. The CFTC requires all large traders to identify themselves as commercial or non-commercial which we, and the previous literature (e.g., Bessembinder (1992) and de Roon, Nijman, and Veld (2000)), refer to as hedgers and speculators. For each futures contract, the long and short open interest held by these traders on Tuesday are reported on a weekly basis.[4]

Using the positions of speculators and hedgers as defined by the CFTC, we define the Net Speculator Position for each asset as follows:

$$\text{Net Speculator Position} = \frac{\text{Speculator Long Positions - Speculator Short Positions}}{\text{Open Interest}}$$

This signed measure shows whether speculators are net long or short in aggregate, and scales their net position by the open interest or total number of contracts outstanding in that futures market. Since speculators and hedgers approximately add up to zero (except for a small difference denoted "non-reported" due to measurement issues of very small traders), we focus our attention on speculators. Of course, this means that net hedger positions constitute the opposite side (i.e., the negative of Net Speculator Position).

The CFTC positions data does not cover all of the futures contracts we have returns for and consider in our analysis. Most commodity and foreign exchange contracts are covered, but only the U.S. instruments among the stock and bond futures contracts are covered. The third and fourth columns of Table 1 report summary statistics on the sample of futures contracts with net speculator positions in each contract over time. Speculators are net long on average, and hence hedgers are net short, for most of the contracts, a result consistent with Bessembinder (1992) and de Roon, Nijman, and Veld (2000) for a smaller set of contracts over a shorter time period. All but one of the commodities (natural gas) have net long speculator positions over the sample period, with

[4] While commercial traders likely predominantly include hedgers, some may also be speculating, which introduces some noise into the analysis in terms of our classification of speculative and hedging trades. However, we see no obvious bias this potential misclassification would impose on any of our results.

silver exhibiting the largest average net long speculator position. This is consistent with Keynes' (1930) conjecture that producers of commodities to be the primary hedgers in markets and to be on the short side of these contracts as a result. For the other asset classes, other than the S&P 500, the 30-year U.S. Treasury bond and the $US/Japanese and $US/Swiss exchange rates, speculators exhibit net long positions on average. Table 1 also highlights that there is substantial variation over time in net speculator positions per contract and across contracts. Not surprisingly, the standard deviation of net speculator positions is positively related to the volatility of the futures contract itself.

The final two columns of Table 1 report the coefficient and *t*-statistic from a regression of the monthly returns on each futures contract on the previous month's net long speculator position in that contract. All the contracts, except for the S&P 500, exhibit a positive coefficient (and 27 out of 29 are statistically significant at the 5% level), indicating that last month's net speculator position forecasts next month's return positively. This result matches that of de Roon, Nijman, and Veld (2000) for a smaller set of contracts over an earlier sample period. This predictability can be interpreted as a premium for liquidity provision to hedgers (who are on the other side of these contracts).

C. Factors

We evaluate the returns of our strategies relative to standard pricing benchmarks, namely the MSCI World equity index, Barclay's Aggregate Bond Index, Goldman Sachs Commodity Index (GSCI), all of which we obtain from Datastream, the long-short factors *SMB*, *HML*, and *UMD* from Ken French's website, and the long-short value and cross-sectional momentum factors across asset classes from Asness, Moskowitz, and Pedersen (2010).

D. Ex-Ante Volatility Estimate

Since volatility varies dramatically across our assets (illustrated in Table 1), we scale the returns by their volatilities in order to make meaningful comparisons across assets. We estimate each instrument's ex-ante volatility σ_t at each point in time using an extremely simple model: the exponentially-weighted lagged squared daily returns (i.e., a simple univariate GARCH model). Specifically, the ex ante annualized variance σ_t^2 for each instrument is calculated as follows:

$$\sigma_t^2 = 261 \cdot \sum_{i=0}^{\infty} (1-\delta)\delta^i \left(r_{t-1-i} - \overline{r}_t\right)^2$$

where the factor 261 scales the variance to be annual, the weights $(1-\delta)\delta^i$ add up to 1, and $\overline{r}_t$ is the exponentially weighted average return computed similarly. The parameter δ is chosen so that the center of mass of the weights is $\sum_{i=0}^{\infty} (1-\delta)\delta^i i = \frac{\delta}{1-\delta} = 60$ days. The volatility model is the same for all assets at all times. While all of the results in the paper are robust to more sophisticated volatility models, we chose this model due to its simplicity and lack of look-ahead bias in the volatility estimate. To ensure no look-ahead bias contaminates our results, we use the volatility estimates at time *t-1* applied to time *t* returns throughout the analysis.

3. Time Series Momentum

We start by examining the time series predictability of futures returns across different time horizons.

A. Regression Analysis: Predicting Price Continuation and Reversal

We regress the excess return r_t^s for instrument *s* in month *t* on its return lagged *h* months, where both returns are scaled by their ex ante volatilities σ_{t-1}^s (defined above in Section 2.D.):

$$r_t^s / \sigma_{t-1}^s = \alpha + \beta_h r_{t-h}^s / \sigma_{t-h-1}^s + \varepsilon_t^s$$

We divide all returns by their volatility to put them on the same scale because they have very different volatilities (as shown in Table 1). This is similar to using Generalized

Least Squares instead of Ordinary Least Squares. Stacking all futures contracts and dates, we run a pooled panel regression and compute *t*-statistics that account for group-wise clustering by time (at the monthly level). The regressions are run using lags of h = 1, 2, ..., 60 months.

Panel A of Figure 1 plots the *t*-statistics from the pooled regressions by month lag h. The positive *t*-statistics for the first 12 months indicate significant return continuation or trends. The negative signs for the longer horizons indicate reversals, the most significant of which occur in the year immediately following the positive trend.

Another way to look at time series predictability is to simply focus only on the *sign* of the past excess return. This even simpler way of looking at time series momentum underlies the trading strategies we consider in the next section. In a regression setting, this strategy can be captured using the following specification:

$$r_t^s / \sigma_{t-1}^s = \alpha + \beta_h sign\left(r_{t-h}^s\right) + \varepsilon_t^s$$

We again make the left-hand side of the regression independent of volatility (the right-hand side is too since *sign* is either +1 or -1), so that the parameter estimates are comparable across instruments. We report the *t*-statistics from a pooled regression with standard errors clustered by time (i.e., month) in Panel B of Figure 1.

The results are similar across the two regression specifications: strong return continuation for the first year and weaker reversals for the next four years. In both cases, the data exhibit a clear pattern, with all of the most recent 12-month lag returns positive (and nine statistically significant) and the majority of the remaining lags negative. Repeating the panel regressions for each asset class separately, we obtain the same patterns: one to 12-month positive trends followed by smaller reversals over the next four years. (We do not report these regressions by asset class for brevity.)

B. Time Series Momentum Strategies by Holding Period and Look-Back Period

We next investigate the profitability of a number of trading strategies based on time series momentum. We vary both the number of months we look back to define the signal used to form the portfolio (the "look-back period") and the number of months we hold each portfolio after it has been formed (the "holding period").

For each instrument s and month t, we consider whether the excess return over the past k months is positive or negative and go long the contract if positive and short if negative, holding the position for h months. We set the position size to be inversely proportional to the instrument's ex-ante volatility, $1/\sigma_{t-1}^{s}$, each month. Sizing each position in each strategy to have constant ex ante volatility is helpful for two reasons. First, it makes it easier to aggregate strategies across instruments with very different volatility levels. Second, it is helpful econometrically to have a time series with relatively stable volatility so that the strategy is not dominated by a few volatile periods.

We then compute a monthly return series for each combination of look-back periods and holding periods (k,h). In particular, for each (k,h), each instrument, and each month, we first compute the average return across *all* portfolios at that time: the return on the portfolio that was constructed last month, the month before that (and still held if the holding period h is greater than two), and so on for all currently "active" portfolios. This return series construction is analogous to that created by Jegadeesh and Titman (1993) for cross-sectional momentum strategies of varying look-back and holding periods. We then average the returns across all instruments (or all instruments within an asset class), to obtain our time series momentum strategy returns, $r_t^{TS-MOM(k,h)}$.

To evaluate the performance of these strategies, we compute the alphas of these portfolios from the following regression:

$$r_t^{TS-MOM(k,h)} = \alpha + \beta_1 MKT_t + \beta_2 BOND_t + \beta_3 GSCI_t + sSMB_t + hHML_t + mUMD_t + \varepsilon_t$$

where we control for passive exposures to the three major asset classes—namely the stock market *MKT*, proxied by the excess return on the MSCI World Index, the bond market *BOND*, proxied by the Barclays Aggregate Bond Index, the commodity market *GSCI*, proxied by the Goldman Sachs Commodity Index—as well as the standard Fama-French stock market factors *SMB, HML,* and *UMD* for the size, value, and (cross-sectional) momentum premia. For the evaluation of time series momentum strategies, we rely on the sample starting in 1985 to ensure that a comprehensive set of instruments have data (see Table 1) and that the markets had significant liquidity. We obtain similar (and generally more significant) results if older data is included.

Table 2 shows the *t*-statistic of the estimated alphas for each asset class and overall across all instruments. The existence and significance of time series momentum is robust across horizons and asset classes, particularly when the look-back and holding periods are 12 months or less. In addition, we confirm that the time series momentum results are almost identical if we use the cash indices for the stock index futures. The other asset classes do not have cash indices.

C. 12-month Time Series Momentum in Depth

For a more in-depth analysis of time series momentum, we focus our attention on a single time series momentum strategy for brevity. Following the convention used in the cross-sectional momentum literature (and based on the results from Figure 1 and Table 2), we focus on the properties of the 12-month time series momentum strategy with a 1-month holding period (e.g., $k = 12$ and $h = 1$), which we refer to simply as TS-MOM. We start by looking at each instrument and asset separately and then pool all the assets together in a diversified TS-MOM portfolio.

We size each position (long or short) so that its ex ante annualized volatility is 0.60%. That is, the position size is chosen to be 0.60% / σ_{t-1}, where σ_{t-1} is the estimate of the ex ante volatility of the contract as described above. The choice of 0.60% is made so that when we combine all the instruments by summing across all asset classes we obtain an ex ante volatility estimate of about 10% per year, which roughly corresponds to the level of annual volatility exhibited by other factors such as those of Fama and French (1993) and Asness, Moskowitz, and Pedersen (2010).[5] This is equivalent to weighting each security in a diversified portfolio of all securities by the inverse of its ex ante volatility so that the resulting portfolio has an ex ante standard deviation of 10% per year.

[5] This translates into a use of margin capital of about 5-20%, which is well within what is feasible to implement in a real-world portfolio.

The scale is inconsequential except for comparing across factors used in other work. The return on the TS-MOM strategy for any instrument *s* is then:

$$r_{t,t+1}^{TS-MOM,s} = sign(r_{t-12,t}^{s})\frac{0.60\%}{\sigma_t^s}r_{t,t+1}^{s}$$

We compute this return for each instrument and each available month from January 1985 to December 2009. Panel A of Figure 2 plots the annualized Sharpe ratios of these strategies for each futures contract. As the figure shows, quite remarkably, *every* single futures contract exhibits positive predictability from past one year returns. All 58 futures contracts exhibit positive time series momentum returns and 52 of them are statistically different from zero.

To test whether this predictability might be driven or exaggerated by illiquidity, Panel B of Figure 2 plots the illiquidity of each futures contract, which we measure using the daily dollar trading volume for each contract. Since assets are vastly different across many dimensions, we first rank each contract within an asset class by their daily trading volume (from highest to lowest) and compute the standard normalized rank of each contract by demeaning each rank and dividing by its standard deviation i.e., (*rank - mean(rank))/std(rank)*. Positive (negative) values imply a contract is more (less) illiquid than the median contract for that asset class. Comparing Panels A and B of Figure 2, there appears to be little relation between the magnitude of the Sharpe ratio of the time series momentum effect for a contract and its illiquidity. In fact, the correlation is -0.16 across all contracts, suggesting that, if anything, *more* liquid rather than less liquid contracts exhibit greater time series momentum profits.

Table 3 examines the risk-adjusted performance of a diversified TS-MOM strategy and its factor exposures. We sum up all the positions from the time series momentum strategies in all contracts to form a well-diversified portfolio of time series momentum across all instruments. Since each strategy in each asset is first scaled to the same constant ex ante volatility, simply adding up the positions treats each strategy equally, resulting in a portfolio with an ex ante volatility of 9.3% per year. Panel A of Table 3 regresses the excess return on the TS-MOM strategy on the returns of the

MSCI World stock market index and the standard Fama-French factors *SMB*, *HML*, and *UMD*, representing the size, value, and cross-sectional momentum premium among individual stocks. The first row reports monthly time series regression results and the second row uses quarterly non-overlapping returns (to account for any non-synchronous trading effects across markets). In both cases, TS-MOM delivers a large and significant alpha or intercept with respect to these factors of about 1.26% per month or 3.8% per quarter. The TS-MOM strategy does not exhibit significant betas on the market, *SMB*, or *HML* but loads significantly positively on *UMD*, the cross-sectional momentum factor. We explore the connection between cross-sectional and time series momentum more fully in the next section, but given the large and significant alpha, it appears that time series momentum is not fully explained by cross-sectional momentum in individual stocks.

Panel B of Table 3 repeats the regressions using the Asness, Moskowitz, and Pedersen (2010) value and momentum "everywhere" factors (i.e., factors diversified across asset classes) in place of the Fama and French factors. Asness, Moskowitz, and Pedersen (2010) form long-short factors of value and momentum across individual equities from four international markets, stock index futures, bond futures, currencies, and commodities. Similar to the Fama and French factors, these are cross-sectional factors. Once again, we find no significant loading on the market index or the global value factor, but significant loading on the cross-sectional momentum everywhere factor. Once again though, the returns to TS-MOM are not fully captured—the alpha is still an impressive 94 basis points per month or 2.65% per quarter and highly statistically significant.

Panel C of Table 3 looks at other, non-priced factors and extreme events to see when TS-MOM is most profitable. We do not report intercepts here because the factors are not always returns. For brevity, we only report quarterly return regressions results. The first row of Panel C of Table 4 reports coefficients on the market index and squared market index. While the beta on the market itself is insignificant, the coefficient on the market squared is significantly positive, indicating that TS-MOM delivers its highest profits during the most extreme market episodes. Figure 3 highlights this result by plotting the TS-MOM returns against the S&P 500 returns. The returns to TS-MOM are largest during the biggest up and down market movements. These results indicate that the positive TS-MOM average returns are not likely to be compensation for crash risk. Indeed, historically, TS-MOM has done well during and shortly after "crashes".

The second row of Panel C of Table 3 reports results using the TED spread, a proxy for funding liquidity as discussed by Brunnermeier and Pedersen (2007), Asness, Moskowitz, and Pedersen (2010), Aschcraft, Garleanu, and Pedersen (2010), and Moskowitz and Pedersen (2010), and the top 20% most extreme realizations of the TED spread to capture the most illiquid funding environments. As the table shows, there is no significant relation between the TED spread and TS-MOM returns, suggesting little relationship with funding liquidity. The third row of Panel C of Table 3 repeats the analysis using the VIX index to capture the level of market volatility and the most extreme market volatility environments. We see no significant relationship between TS-MOM profitability and market volatility either.

At the bottom of Panel C of Table 3, we examine the relationship between TS-MOM returns and sentiment index measures used by Baker and Wurgler (2006, 2007). We examine both the level of sentiment and its monthly changes (first differences) and examine the top and bottom extremes (20%) of these variables. As the regressions indicate, we find little relationship between TS-MOM profitability and sentiment measures, even at the extremes.

Lastly, we consider the cumulative excess return to the diversified time series momentum strategy over time in Figure 4 (on a log scale). For comparison, we also plot the cumulative excess returns of a diversified passive long position in all instruments, with an equal amount of risk in each instrument. (Since each instrument is scaled by the same constant volatility, both portfolios would have the same ex ante volatility except for the differences in correlations among time series momentum strategies and passive long exposures.)

As Figure 4 shows, the performance over time of the diversified time series momentum strategy provides a relatively steady stream of positive returns. The magnitude and consistency of these time series momentum returns appear difficult to rationalize under a pure risk-based asset pricing model. The diversified passive long portfolio produces terminal wealth about one third the size of time series momentum.

These results also reflect significant diversification benefits across each instrument's time series momentum strategies. This is due to a small, but positive, correlation as we analyze next.

D. *Correlation Structure*

Table 4 examines the correlation structure of the time series momentum strategies and compares them to the correlation structure of passive long positions in the contracts. The first row of Panel A of Table 4 reports the average pair-wise correlation of times-series momentum returns among contracts within the same asset class. The correlations are positive within each asset class, ranging from 0.37 to 0.38 for equities and fixed income futures to 0.10 and 0.07 for commodities and currencies. Part of this comovement structure reflects the comovement of the returns to simply being passive long (or short) each instrument at the same time. The second row of Panel A of Table 4 reports the average pair-wise correlation of passive long positions within each asset class. Except for currencies, passive long strategies exhibit higher correlations than time series momentum strategies. The comovement of the passive strategies is closely related to the correlation of positions of time series momentum strategies (where positions are a series of ones and negative ones). The average correlation of positions mirrors the correlations of the passive long returns. These results indicate that a diversified portfolio of time series momentum on these futures contracts provides more diversification than a portfolio of passive long positions across all assets, contributring to the consistent returns seen in Figure 4 as discussed above.

Panel B of Table 4 shows the average correlation of time series momentum strategies *across* asset classes. Here, we first compute the return of a diversified portfolio of time series momentum strategies within each asset class and then estimate the correlation of returns for diversified TS-MOM portfolios across asset classes. All of these correlations are positive, ranging from 0.08 to 0.20. For comparison, the table also shows the correlations across asset classes of diversified passive long positions. In each case, we see that the correlations of times-series momentum strategies across asset classes are larger than the corresponding correlations of passive longs, many of which are negative.

Summing up the results from both panels, time series momentum strategies are positively correlated within an asset class, but less so than passive long strategies. However, across asset classes, time series momentum strategies exhibit positive correlation with each other, while passive long strategies exhibit zero or negative correlation across asset classes. This suggests there is a small common component affecting times-series momentum strategies across asset classes at the same time that isn't present in the underlying assets themselves, similar to the findings of Asness, Moskowitz, and Pedersen (2010) for cross-sectional momentum strategies across different asset classes.

4. Time Series vs. Cross-Sectional Momentum

Our previous results show a significant relationship between time series momentum and cross-sectional momentum. In this section we explore that relationship further and determine how much overlap and difference exist between our time series momentum strategies and the cross-sectional momentum strategies used in the literature.

A. Time Series Momentum Regressed on Cross-Sectional Momentum

Panel A of Table 5 provides further evidence on the relationship between time series momentum (TS-MOM) and cross-sectional momentum (XS-MOM) by regressing the returns to our time series momentum strategies—diversified across all instruments and within each asset class—on the returns of cross-sectional momentum strategies applied to the same assets. Specifically, following Asness, Moskowitz, and Pedersen (2010), we apply a cross-sectional momentum strategy based on the relative ranking of each asset's past 12-month returns and form portfolios that go long or short the assets in proportion to their ranks relative to the median rank.[6]

[6] Asness, Moskowitz, and Pedersen (2010) exclude the most recent month when computing 12-month cross-sectional momentum. For consistently, we follow that convention here, but our results do not depend on whether the most recent month in excluded or not.

The first row of Panel A of Table 5 reports results from the TS-MOM strategy diversified across all assets regressed on the XS-MOM strategy that is diversified across those same assets. As before, time series momentum and cross-sectional momentum are significantly related, with the beta of TS-MOM on XS-MOM equal to 0.57 with a *t*-statistic of 15.52. However, as the intercept indicates, TS-MOM is not fully captured by XS-MOM, exhibiting a positive and significant alpha of 66 basis points per month with a *t*-statistic of 5.64. So, TS-MOM and XS-MOM are related, but not the same thing.

The second row of Panel A of Table 5 repeats the regression using XS-MOM strategies for each asset class, including individual stocks. Once again, TS-MOM is related to XS-MOM across all of the different asset classes, even to individual equities that are not even included in the TS-MOM strategy and after controlling for exposure to XS-MOM from the other four asset classes. Further, TS-MOM still exhibits significant excess returns not captured by these cross-sectional momentum strategies.

Repeating these regressions using the TS-MOM returns for each asset class separately, we find a consistent pattern. TS-MOM and XS-MOM are related within each asset class, but TS-MOM is not captured by XS-MOM, as the alphas all remain significantly positive across asset classes, and with R-squares are ranging from 60% in FX to 12% in fixed income. We also see some interesting cross-asset relationships among TS- and XS-MOM. For instance, not only is TS-MOM for commodities correlated with XS-MOM for commodities, but also XS-MOM for currencies. Likewise, TS-MOM among equity index futures is correlated with XS-MOM among those equity indexes but also with XS-MOM among individual stocks. And, TS-MOM for fixed income is correlated with XS-MOM for fixed income and XS-MOM for equity indexes. These results indicate significant correlation structure in time series and cross-sectional momentum across different asset classes, consistent with our earlier results and those of Asness, Moskowitz, and Pedersen (2010).

B. A Simple, Formal Decomposition

We can more formally write down the relationship between times-series (TS-MOM) and cross-sectional (XS-MOM) momentum. Following Lo and MacKinlay (1990) and

Lewellen (2002), we can describe a simple cross-sectional and time series momentum strategy on the same assets as follows. For cross-sectional momentum, we let the portfolio weight of instrument i be $w_t^{XS,i} = \frac{1}{N}(r_{t-12,t}^i - r_{t-12,t}^{EW})$, that is, the past 12-month excess return over the equal-weighted average return, $r_{t-12,t}^{EW} = \frac{1}{N}\sum_{i=1}^{N} r_{t-12,t}^i$. The return to the portfolio is therefore

$$r_{t,t+1}^{XS} = \sum_{i=1}^{N} w_t^{XS,i} r_{t,t+1}^i$$

Next, assuming that the monthly expected return is[7] $\mu^i = E(r_{t,t+1}^i) = E(r_{t-12,t}^i)/12$ and letting $\mu = [\mu^1,...,\mu^N]'$, $R_{t,s} = [r_{t,s}^1,...,r_{t,s}^N]'$, and $\Omega = E[(R_{t-12,t} - 12\mu)(R_{t,t+1} - \mu)']$, the expected return to cross-sectional momentum can be decomposed as

$$\begin{aligned} E[r_{t,t+1}^{XS}] &= \frac{tr(\Omega)}{N} - \frac{1'\Omega 1}{N^2} + 12\sigma_\mu^2 \\ &= \frac{N-1}{N^2} tr(\Omega) - \frac{1}{N^2}[1'\Omega 1 - tr(\Omega)] + 12\ \sigma_\mu^2 \end{aligned}$$

where *tr* is the trace of a matrix (i.e., the sum of the diagonal elements), **1** is an ($N \times 1$) vector of ones (i.e., $1'\Omega 1$ is the sum of all elements of Ω), and σ_μ^2 is the cross-sectional variance of the mean monthly returns μ^i.

This equation shows that cross-sectional momentum profits can be decomposed into an auto-covariance component between lagged 1-year returns and future 1-month returns (the diagonal elements of Ω captured by the first term), a cross-covariance component capturing the temporal leads and lags across stocks (the off-diagonal elements of Ω captured by the second term), and the cross-sectional variation in unconditional mean returns (the third term). As emphasized by Lewellen (2002), cross-sectional momentum profits need not be generated by positive autocorrelation in returns (i.e., time series predictability). If cross-serial covariances across stocks are negative, implying that high past returns of an asset predict lower future returns of other assets, this, too, can lead to momentum profits. Likewise, large cross-sectional variation in mean returns can also

[7] This relation between mean returns is exact if annual returns are computed by summing over monthly returns. If returns are compounded, this relation is approximate, but an exact relation is straightforward to derive, e.g. using the separate means of monthly and annual returns.

lead to momentum profits since on average assets with the highest mean returns will have the highest realized returns.

The returns to time series momentum can be decomposed similarly if we let the portfolio weights be $w_t^{TS,i} = \frac{1}{N} r_{t-12,t}^i$. Then the expected return is:

$$
\begin{aligned}
E\left(r_{t,t+1}^{TS}\right) &= E\left(w_t^{TS,i} r_{t,t+1}^i\right) \\
&= \frac{tr(\Omega)}{N} + 12\frac{\mu'\mu}{N}
\end{aligned}
$$

As these equations highlight, time series momentum profits are primarily driven by time series predictability or positive auto-covariance in returns if the average squared mean returns of the assets is small. Comparing the two sets of equations, we see that time series momentum profits can be decomposed into the auto-covariance term that also underlies cross-sectional momentum (plus the average squared mean excess return). The equations thus provide a link between time series and cross-sectional momentum profitability, which we can measure in the data to determine how related these two phenomena are.

Panel B of Table 5 computes each of the components of the diversified 12-month cross-sectional and time series momentum strategies across all assets and within each asset class according to the above equations. We report the three components of the cross-sectional momentum strategy: "Auto" refers to the autocovariance or time series momentum component, "Cross" refers to the cross-serial covariance or lead-lag component, and "Mean" refers to the contribution from unconditional mean returns, as well as their sum ("Total"). We also report the two components to TS-MOM: the Auto and mean squared return components, as well as their sum.

As Panel B of Table 5 shows, time series and cross-sectional momentum are related but different. The auto-covariance component contributes just about all of the cross-sectional momentum strategy profits across all assets. The cross-serial or lead-lag component contributes *negatively* and the cross-sectional variation in means has a small positive contribution to overall cross-sectional momentum profits. The contribution of these components to cross-sectional momentum strategies is also fairly stable across asset classes, with the dominant component consistently being the auto-covariance or time series piece.

The decomposition of time series momentum shows that the main component is naturally auto-covariance. Squared mean excess returns is a smaller component, and this is true in all asset classes except fixed income, where squared mean excess returns have been substantial over this sample period.

We can also regress the returns of time series momentum defined as in the decomposition (which is linear as opposed to using the sign as we did above) on the returns to cross-sectional momentum defined in the decomposition, and vice versa. Doing this, we find as in Panel A that time series momentum has a significant alpha to cross-sectional momentum, but not the other way. (For brevity we omit these results.)

C. Implications for Theory

The significant time series momentum effect we document has potentially important implications for theories of asset pricing. First, from an efficient markets standpoint, the existence of time series momentum rejects the random walk hypothesis. Hence, to reconcile this time series predictability with efficient markets, significant time-varying risk premia must be present. While we can't rule out that time-varying risk premia could be partly driving our results, the magnitude of our time series momentum profits, as well as the diversity of asset classes for which we find them, would seem to present a significant challenge to existing risk-based theories. Existing risk models, for instance, have a tough time explaining why time-varying risk premia are so large and so consistent across very different asset classes and markets, and why they change so rapidly (within a year). While researchers have grappled for decades on the size of return premia found in the data (e.g., Hansen and Singleton (1982), Mehra and Prescott (1985), and Hansen and Jagannathan (1997)), where time series momentum presents yet another puzzle, the consistency of this premium across very different assets with very different risk exposures adds an additional hurdle for an asset pricing model to meet.

Behavioral theories of asset pricing, too, must meet these challenges. Prominent behavioral models have typically focused on a single asset, making predictions about the time series predictability of returns for that asset (Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)). In this sense, our study of time series momentum is a more direct test of some of these behavioral models than many of the cross-sectional asset pricing anomalies that motivate them. However, behavioral explanations also need to explain the consistency of these patterns across very different assets and markets that may be traded by very different types of investors. If the same behavioral phenomenon is the source of time series momentum, why might different investors from diverse markets be affected by the same behavior in the same way?

Our results also confront some of the theories proposed for cross-sectional momentum. As mentioned above, many of the theories for cross-sectional momentum are actually models of a single asset, and hence better suited for time series momentum. This is true of both the behavioral theories (Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)), and rational theories of momentum (Berk, Green, and Naik (1999), Johnson (2002), Ahn, Conrad, and Dittmar (2003), Zhang (2004), and Sagi and Seasholes (2007)). Moreover, the underlying mechanism for momentum in many of these risk models revolves around the investment growth options and cash flow dynamics of a single firm. It is difficult to see how those same mechanisms would apply to currencies or commodities, for example.

The relation between time series and cross-sectional momentum can help shed further light on these theories and what factors might be driving return predictability in general. For example, underreaction stories such as Barberis, Shleifer, and Vishny (1998) or Hong and Stein (1999) predict positive autocorrelation in returns, which our decomposition shows is an essential part of time series momentum, and hence a more direct test of underreaction. The initial positive trends followed by the reversals after a year could be consistent with delayed overreaction as well (Daniel, Hirshleifer, and Subrahmanyam (1998)). Our decomposition may further help distinguish these theories. As Lewellen (2002) shows, both overreaction and time-varying risk premia can drive excess co-movement among assets that could generate negative cross-serial correlation that can contribute to the profitability of a cross-sectional momentum strategy. However, we show that these cross-asset lead-lag effects do not influence a time series momentum strategy. Moreover, we find cross-serial covariances among our futures contracts to be a *negative* contributor to cross-sectional momentum returns. Hence, the main time series predictor of returns among our instruments appears to be an asset's own lagged return.

These results differ from those of Lewellen (2002) who examines individual equity portfolios of industries and size and value portfolios and finds that most of the XS-MOM profitability comes from the Cross component. On the other hand, Chen and Hong (2002) find auto-covariance to be more important for stock momentum using a different decomposition. We find that among our instruments, not only is the autocorrelation component the most important contributor to XS-MOM, but in fact the cross-covariance component contributes negatively to XS-MOM among our instruments. Since our assets and futures contracts are quite different from the portfolios used by Lewellen (2002), it is possible that different assets exhibit different time series return properties. It would be interesting to further investigate these issues and why, from a theoretical perspective, different assets may exhibit different momentum structures.

Conrad and Kaul (1998), on the other hand, argue that cross-sectional variation in mean returns is a significant contributor to momentum profits among individual stocks, though Moskowitz and Grinblatt (1999), Grundy and Martin (2001), Jegadeesh and Titman (2001), and Lewellen (2002) overturn this finding. Our results from these futures contracts also indicate that cross-sectional variation in mean returns is not a significant contributor to momentum profitability.

While a full theoretical explanation accommodating all these facts is well beyond the scope of this paper, in the next section we begin to scratch the surface of what might be driving the time series momentum of our futures contracts by looking at trading positions of speculators and hedgers from the CFTC data.

5. Who Trades on Trends: Speculators or Hedgers?

To consider who trades on trends, Figure 5 shows the Net Speculator Position broken down by the sign of the past 12-month return for each instrument with available CFTC data. Specifically, for each futures contract, Figure 5 plots the average Net Speculator Position in, respectively, the sub-sample where the past 12 month return on the contract was positive ("Positive TS-MOM") and negative ("Negative TS-MOM") de-meaned using the average Net Speculator Position for each instrument. The figure illustrates that speculators are on average positioned to benefit from trends, whereas hedgers, by definition, have the opposite positions. Speculators have longer-than-average positions following positive past 12-month returns, and smaller-than-average positions following negative returns, on average. Said differently, speculators have larger positions in an instrument following positive returns than following negative returns. This trend-following pattern of speculative positions is found for every contract except the S&P 500 futures, where Net Speculator Positions have opposite signs, though are close to zero. Since we also know that trend following is associated with positive abnormal returns, these results indicate that speculators profit on average from these position changes at the expense of hedgers.

A. The Evolution of a Trend

We next consider the dynamics of these trading positions over time. Our previous results suggest that trends or time series momentum lasts about a year and then starts to reverse. We investigate these return patterns in more depth and attempt to link them to the evolution of trading positions.

Examining the evolution of trends and trading patterns may help distinguish theories. For example, if initial under-reaction to news is the cause of trends, then this part of the trend should *not* reverse, whereas the part of a trend that is driven by over-reaction *should* reverse as prices eventually gravitate back toward fundamentals.

To consider the evolution of a trend, we perform an event study of our time series momentum strategy as follows. For each month and instrument, we first identify whether the previous 12 months excess returns are positive or negative. For all the time-instrument pairs with positive 12-month past returns, we compute the average return from 12 months prior to the "event date" (portfolio formation date) to 36 months after. We do the same for the time-instrument pairs with negative past 12-month returns. We then standardize the returns to have a zero mean across time and across the two groups (for ease of comparison), and compute the cumulative returns of the subsequent months following positive past year returns ("Positive TS-MOM") and negative past year returns ("Negative TS-MOM"), respectively, where we normalize the cumulative returns to be 1 at the event date.

Panel A of Figure 6 shows the cumulative returns conditional on positive and negative time series momentum. The returns to the left of the event date are, of course, positive and negative by construction. To the right of the event date, we see that the positive pre-formation returns continue upward after the portfolio formation for about a year, consistent with a time series momentum effect, and then partially reverse thereafter. This is consistent with both initial under-reaction and delayed over-reaction as predicted by the sentiment theories. While the reversal after a year suggests over-reaction, the fact that only part of the post-formation upward trend is reversed suggests that under-reaction appears to be part of the story. Similarly, the negative pre-formation trend is continued for a year until it partially reverses as well.

Panel B of Figure 6 shows the evolution of Net Speculator Positions that coincide with the positive and negative times-series momentum returns. Specifically, for each instrument and month, we compute the average Net Speculator Position for each month from 12 months prior to the event (portfolio formation date) to 36 months after for both positive and negative trends. We see that for positive TS-MOM, speculators increase their positions steadily from months -12 to 0, building up to the formation date. Likewise, speculators decrease their positions steadily for the negative TS-MOM event date. These patterns are not by construction since we are splitting our sample based on returns and not based on Net Speculator Positions. After the event, speculators' positions begin to mean-revert towards their (positive) average levels, and plateau at about a year (and maybe slightly longer for negative TS-MOM), which is when the trend in returns starts to reverse.

These patterns suggest that while speculator positions are consistent with trading on trends, they do not appear to keep piling into the trade with a lag. In fact, they appear to reduce their trend chasing up to the point where positive returns from following trends disappear. Conversely, hedgers, who are on the other side of these trades, appear to be increasing their positions steadily in the direction of the trend. This suggests that if overreaction is caused by such trading, it would have to come from hedgers, not speculators. While the direction of causality between returns and trading positions is indeterminate, these results also suggest that trading positions of speculators and hedgers are closely linked to the profitability of time series momentum, where speculators appear to be profiting from trends and reversals at the expense of hedgers.

B. Joint Dynamics of Returns and Trading Positions

For a more formal analysis of trading patterns and returns, we study the joint dynamics of time series momentum returns and the change in Net Speculator Positions using a vector autoregressive (VAR) model. We estimate a monthly bivariate VAR with 24 months of lags of returns and changes in Net Speculator Positions and plot the impulse response of returns and Net Speculator Positions from a return shock. We perform a Cholesky decomposition of the variance-covariance matrix of residuals with the return first, and consider a one standard deviation shock to the returns of the contract. The response to this impulse is plotted in Figure 7, both in terms of the effect on the cumulative return to the contract and the cumulative changes in Net Speculator Positions. As the figure shows, returns continue to rise for about a year and then partially reverse thereafter following the return shock. Net Speculator Positions increase contemporaneously with the return shock and then mean-revert to zero by about a year and turn slightly negative for the next two years. These results are consistent with our previous findings and confirm that speculative positions match the return patterns of time series momentum. Speculators seem to profit from trends for about a year and then reverse their positions at the same time momentum reverses—all at the expense of hedgers.

These patterns indicate that speculators are profiting from time series momentum, while hedgers are paying for it. One explanation for this might be that speculators earn a premium through time series momentum by providing liquidity to hedgers. We explore this possibility further by examining the predictability of returns using trading positions as well as different components of futures returns. Namely, whether changes in the underlying spot price or shape of the futures curve (e.g, "roll yield") are driving the time series predictability and how each of these lines up with trading positions.

C. Predictability of Positions, Price Changes, and Roll Yield

We decompose the past return of each futures contract into the change in the price of the underlying spot asset and the return that is related to the shape of the futures curve, called the “roll return” or “roll yield”. We do this as follows. First, we define the underlying spot price changes in excess of the risk-free rate as:

$$\text{price change}_{t-12,t} = \frac{\text{price}_t - \text{price}_{t-12}}{\text{price}_{t-12}} - r^f_{t-12,t}$$

where the prices are measured as the most liquid futures price and $r^f_{t-12,t}$ is the risk-free interest-rate over the 12-month periode. We then define the roll return by the following decomposition:

$$\text{futures return}_{t-12,t} = \text{price change}_{t-12,t} + \text{ roll return}_{t-12,t}$$

In financial futures with little storage costs or convenience yield the roll return defined this way is close to zero, but, in commodity markets, the roll return can be substantial.

Our conjecture is that hedgers’ price pressure affects mostly the roll returns, whereas information diffusion affects mostly price changes. To see why, recall first Keynes’ basic idea that hedging pressure must affect required returns to give speculators an incentive to provide liquidity by taking the other side of the trade. Since hedging takes place in futures markets, hedging pressure would affect futures prices and thus lead to a roll yield as each futures contract expires at the spot price. When hedgers, such as commodity producers, are shorting the futures, this leads to positive roll return and what Keynes called “normal backwardation”. On the other hand, information diffusion (which is the driver of several of the behavioral theories), would simply affect price changes.

Panel B of Figure 7 plots the impulse response of spot price changes and Net Speculator Positions by repeating the VAR we ran above, replacing the total futures returns with the spot price changes only. The impulse response of spot returns and Net Speculator Positions matches those for total returns: trends exist for about a year and then reverse and net speculative positions mirror that pattern. This is consistent with initial under-reaction and delayed over-reaction being due to information diffusion rather than hedging pressure.

Panel C of Figure 7 plots the impulse response from replacing total returns with the roll return in the VAR. Here, the picture looks quite different. A shock to roll returns is associated with a continued upward trend to roll returns and a small effect on Net Speculator Positions. This is consistent with hedgers having stable positions in the same direction for extended time periods and being willing to give up roll returns to enjoy hedging benefits. Speculators who take the other side, profit from momentum as a premium for providing liquidity to hedgers.

Finally, Table 6 revisits the return predictability regressions we started with, focusing on 12-month return predictability, but examines the predictive power of the spot versus roll return, as well as their interaction with speculative trading positions. We regress the return of each futures contract on the past 12 month return of each contract, the spot price change of each contract, the roll return of each contract, and the change in Net Speculator Position. The first four rows of Table 6 report the univariate regression results for each of these variables. The total return, spot price return, roll return, and change in net speculator positions are all significant positive univariate predictors of futures returns.

In multivariate regressions, however, the change in net speculator positions drops slightly and becomes insignificant, indicating that controlling for past returns reduces some of the predictive power of speculative positions. This is consistent with the idea that roll return and speculator positions both capture hedging pressure, though measured differently and neither being a perfect measure. We also see that since spot price changes and roll returns have almost the same predictive regression coefficient, their joint predictive power (as measured by the *R*-square) is the same as the univariate predictability of their sum, which is the total futures return. Finally, the last row of Table

6 includes interaction terms between the spot and roll returns and net speculative positions. While all the coefficients are positive, indicating that when changes in net speculative positions move in the same direction as returns this is a stronger positive predictor of future returns, the results are not statistically significant.

The results indicate that time series momentum is not purely driven by one component of futures returns. Both the spot return change and roll yield provide predictive power for futures returns. In addition, as the VAR results show, there is an interesting dynamic between time series momentum and net speculative and hedging positions. Speculators seem to ride the trend for about a year, eventually reducing their positions and taking the opposite side before the trend reverses. In the process, they earn positive excess returns at the expense of hedgers, who may be willing to compensate speculators for liquidity provision in order to maintain their hedge.

6. Conclusion

We document a significant time series momentum effect that is remarkably consistent across the nearly five dozen futures contracts and several major asset classes we study over the last thirty years. The time series momentum effect is distinct from cross-sectional momentum, though the two are related. Decomposing both time series and cross-sectional momentum profits, we find that the dominant force to both strategies is significant positive auto-covariance between a security's excess return next month and its own lagged 1-year excess return. This evidence is consistent with initial under-reaction stories, but may also be consistent with delayed overreaction theories of sentiment as the time series momentum effect partially reverses itself after one year.

Time series momentum exhibits strong and consistent performance across many diverse asset classes, has small loadings on standard risk factors, and performs well in extreme periods. This evidence presents a challenge to the random walk hypothesis and to standard risk models. The evidence also presents a challenge to current behavioral theories since the markets we study vary widely in terms of the type of investors, yet the pattern of returns remains remarkably consistent across these markets. In addition, we find that the correlation of time series momentum across very different asset classes is stronger than the correlation of passive long positions across those same asset classes, implying the existence of a common component to time series momentum strategies that is not present in the underlying assets themselves—another fact theory should accommodate.

We document a strong link between time series momentum returns and the positions of speculators and hedgers. We find that speculators profit from time series momentum—following the trend in returns to the point where the trend reverses—at the expense of hedgers who are on the opposite side of these trades. This evidence is consistent with speculators earning a premium via time series momentum for providing liquidity to hedgers. Further, we separate futures returns into the effect of price changes, capturing information dissemination, and the roll return, capturing how hedging pressure affects the shape of the futures curve. We find that shocks to both price changes and roll returns are associated with time series momentum, but only the shocks to price changes partially reverse, consistent with behavioral theories of delayed over-reaction applying to information dissemination, not hedging pressure.

Time series momentum represents a more direct test of the random walk hypothesis and a number of prominent behavioral and rational asset pricing theories. Hence, our findings present direct evidence for these models that we hope future work will address.

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Appendix A: Data Sources

Equity Indices. The universe of equity index futures consists of the following 9 developed equity markets: SPI 200 (Australia), CAC 40 (France), DAX (Germany), FTSE/MIB (Italy), TOPIX (Japan), AEX (Netherlands), IBEX 35 (Spain), FTSE 100 (U.K.), and S&P 500 (U.S). Futures returns are obtained from Datastream. We use MSCI country level index returns prior to the availability of futures returns.

Bond Indices. The universe of bond index futures consists of the following 13 developed bond markets: Australia 3-year Bond, Australia 10-year Bond, Euro Schatz, Euro Bobl, Euro Bund, Euro Buxl, Canada 10-year Bond, Japan 10 year Bond (TSE), Long Gilt, US 2-year Note, US 5-year Note, US 10-year Note and US Long Bond. Futures returns are obtained from Datastream. We use JP Morgan country level bond index returns prior to the availability of futures returns. We scale daily returns to a constant duration of 2 years for 2 and 3-year bond futures, 4 years for 5-year bond futures, 7 years for 10-year bond futures and 20 years for 30-year bond futures.

Currencies. The universe of currency forwards covers the following 10 exchange rates:, Australia, Canada, Germany spliced with the Euro, Japan, New Zealand, Norway, Sweden, Switzerland, U.K., and U.S. We use spot and forward interest rates from Citigroup to calculate currency returns going back to 1989 for all the currencies except for CAD and NZD, which go back to 1992 and 1996. Prior to that, we use spot exchange rates from Datastream and IBOR short rates from Bloomberg to calculate returns.

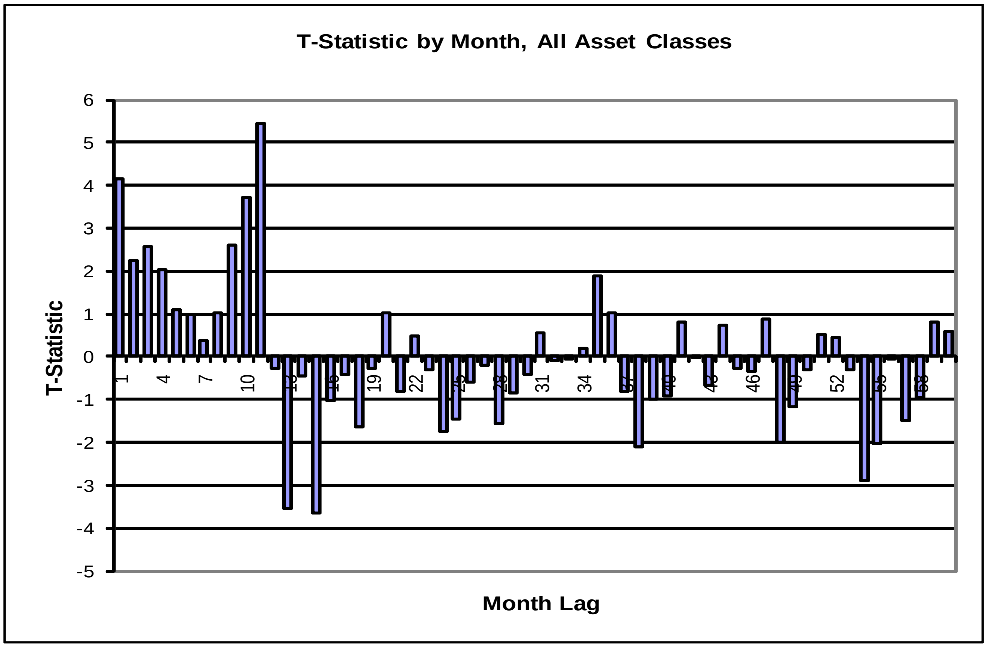
Commodities. We cover 24 different commodity futures. Our data on Aluminum, Copper, Nickel, Zinc is from London Metal Exchange (LME), Brent Crude, Gas Oil, Cotton, Coffee, Cocoa, Sugar is from Intercontinental Exchange (ICE), Live Cattle, Lean Hogs is from Chicago Mercantile Exchange (CME), Corn, Soybeans, Soy Meal, Soy Oil, Wheat is from Chicago Board of Trade (CBOT), WTI Crude, RBOB Gasoline spliced with Unleaded Gasoline, Heating Oil, Natural Gas is from New York Mercantile Exchange (NYMEX), Gold, Silver is from New York Commodities Exchange (COMEX), and Platinum from Tokyo Commodity Exchange (TOCOM).

Speculator Positioning Data. We obtain speculator net length and open interest data from the CFTC Commitments of Traders Report website for the following futures: Corn, Soybeans, Soy Meal, Soy Oil, Wheat traded on Chicago Board of Trade (CBOT), Live Cattle, Lean Hogs, Feeder Cattle, Australian Dollar, Canadian Dollar, Swiss Franc, British Pound, Japanese Yen, Euro FX, New Zealand Dollar, S&P 500 traded on Chicago Mercantile Exchange (CME), Cotton, Coffee, Cocoa, Sugar traded on Intercontinental Exchange (ICE), WTI Crude, RBOB Gasoline spliced with Unleaded Gasoline, Heating Oil, Natural Gas traded on New York Mercantile Exchange (NYMEX) and Gold, Silver traded on New York Commodities Exchange (COMEX). The data cover the period January, 1986 to December, 2009.

Fig. 1. **Time Series Predictability Across All Asset Classes**

We regress the monthly excess return of each contract on its own lagged excess return over various horizons. Panel A uses the size of the lagged excess return as a predictor, where returns are scaled by their ex ante volatility to make them comparable across assets, and Panel B uses the sign of the lagged excess return as a predictor, where the dependent variable is scaled by its ex ante volatility to make the regression coefficients comparable across different assets. Reported are the pooled regression estimates across all instruments with *t*-statistics computed using standard errors that are clustered by time (month).

Panel A: $r_t^s / \sigma_{t-1}^s = \alpha + \beta_h r_{t-h}^s / \sigma_{t-h-1}^s + \varepsilon_t^s$



Panel B: $r_t^s / \sigma_{t-1}^s = \alpha + \beta_h sign\left(r_{t-h}^s\right) + \varepsilon_t^s$

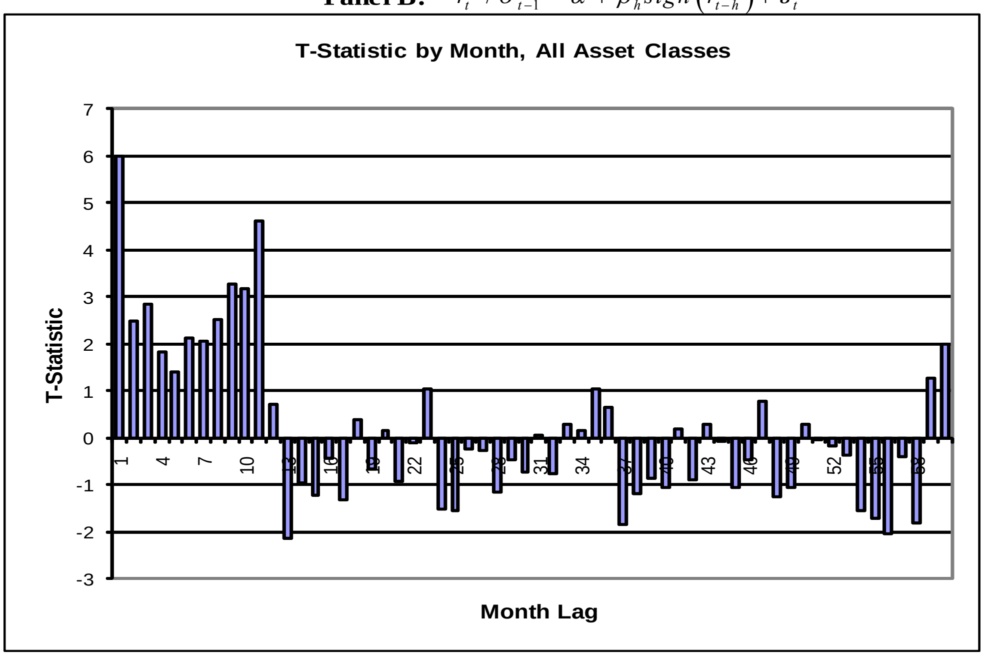
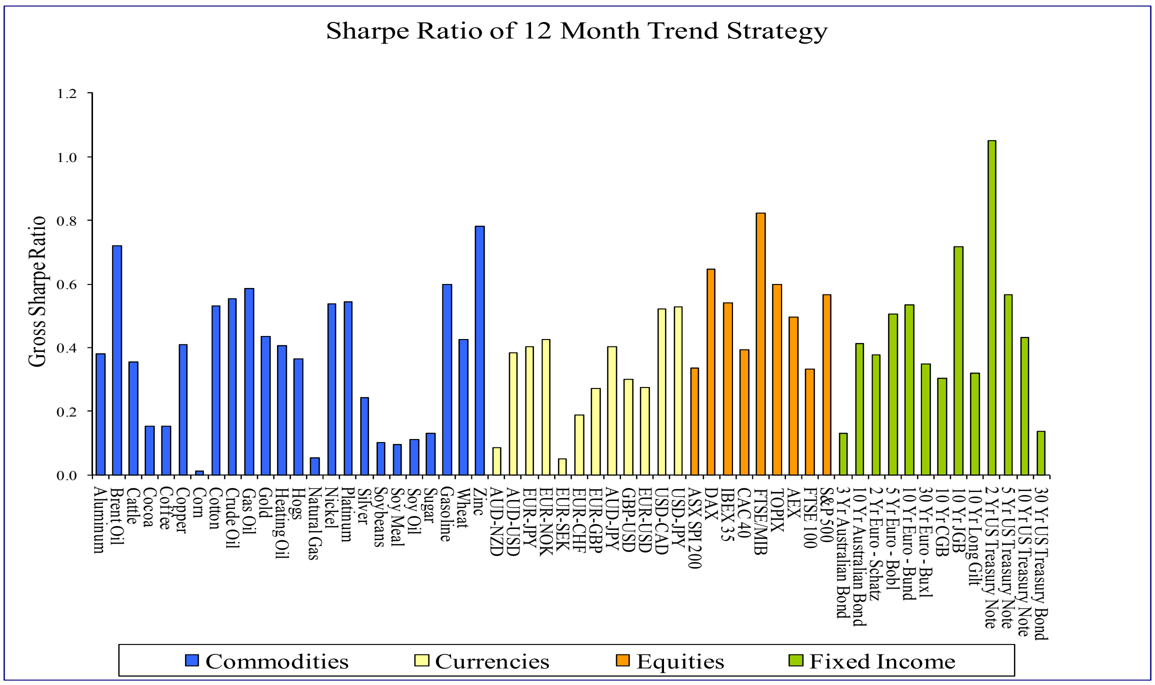


Fig. 2. **Sharpe Ratio of 12-Month Time Series Momentum by Instrument**
Reported are the annualized gross Sharpe ratio of the 12-month time series momentum or trend strategy for each futures contract/instrument. For each instrument in every month the trend strategy goes long (short) the contract if the excess return over the past 12 months of being long the instrument is positive (negative), and scales the size of the bet to be inversely proportional to the ex ante volatility of the instrument to maintain constant volatility over the entire sample period from January 1985 to December 2009. The second figure plots a normalized value of the illiquidity of each futures contract measured by ranking contracts within each asset class by their daily trading volume (from highest to lowest) and reporting the standard normalized rank for each contract within each asset class. Positive (negative) values imply the contract is more (less) illiquid than the median contract for that asset class.



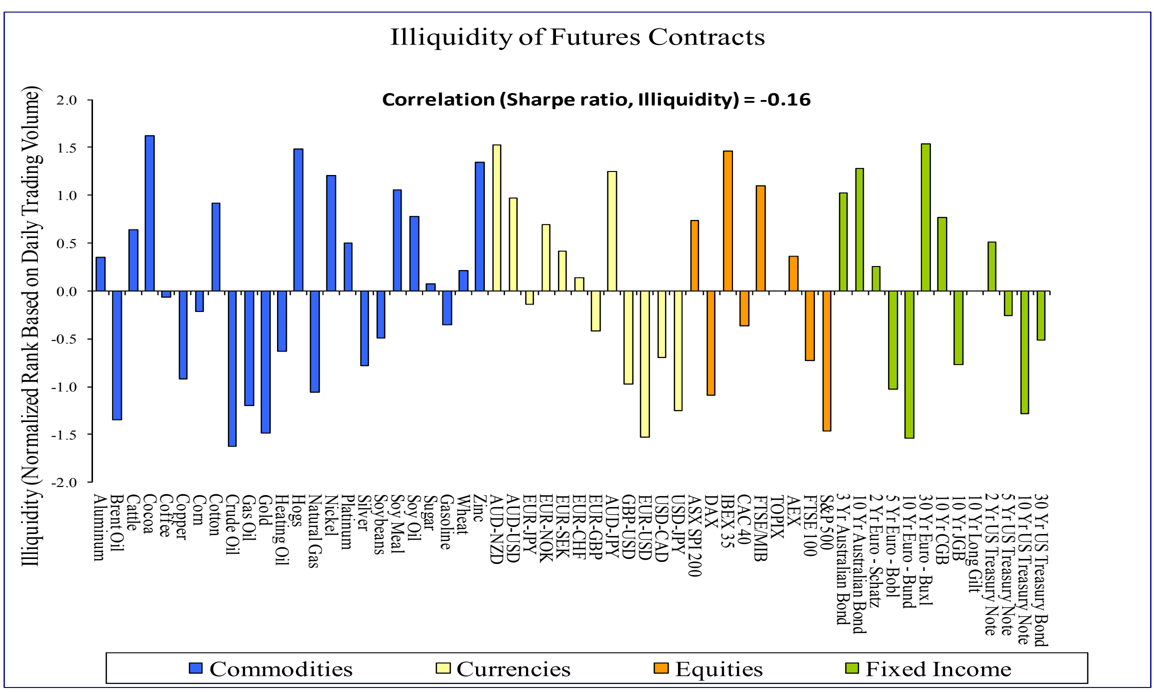


Fig. 3. **The Trend Smile**

The non-overlapping quarterly returns on the diversified (equally weighted across all contracts) 12-month time series momentum or trend strategy are plotted against the contemporaneous returns on the S&P 500.

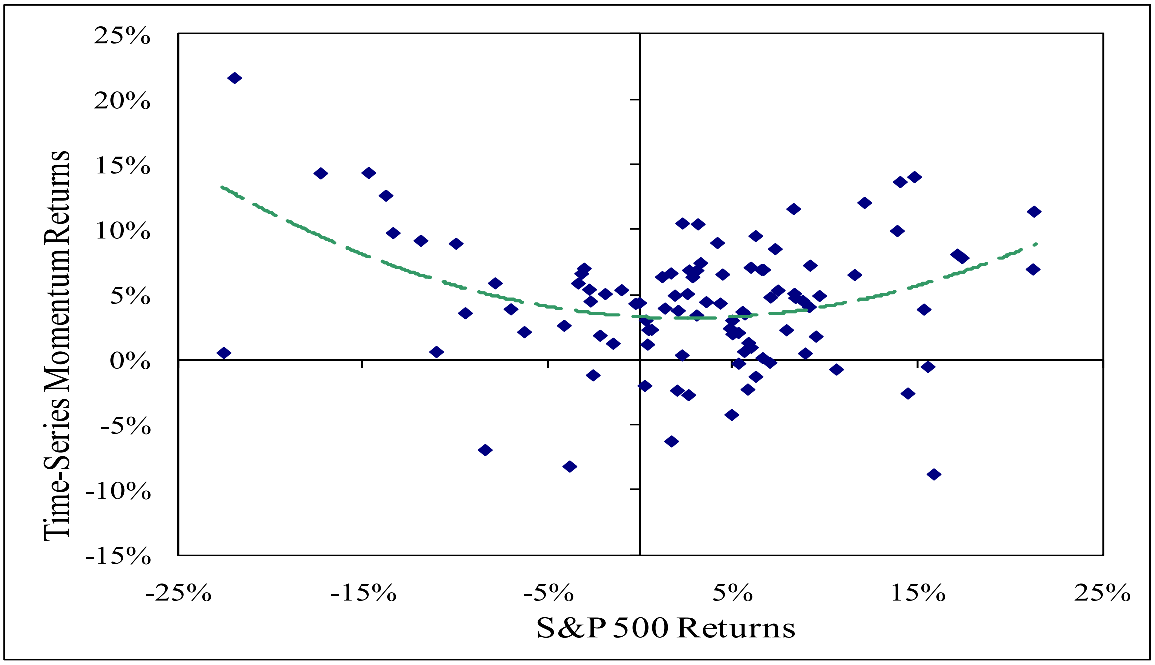


Fig. 4. **Cumulate Exesss Return of Time Series Momentum and Diversified Passive Long Strategy, January 1985 to December 2009.**

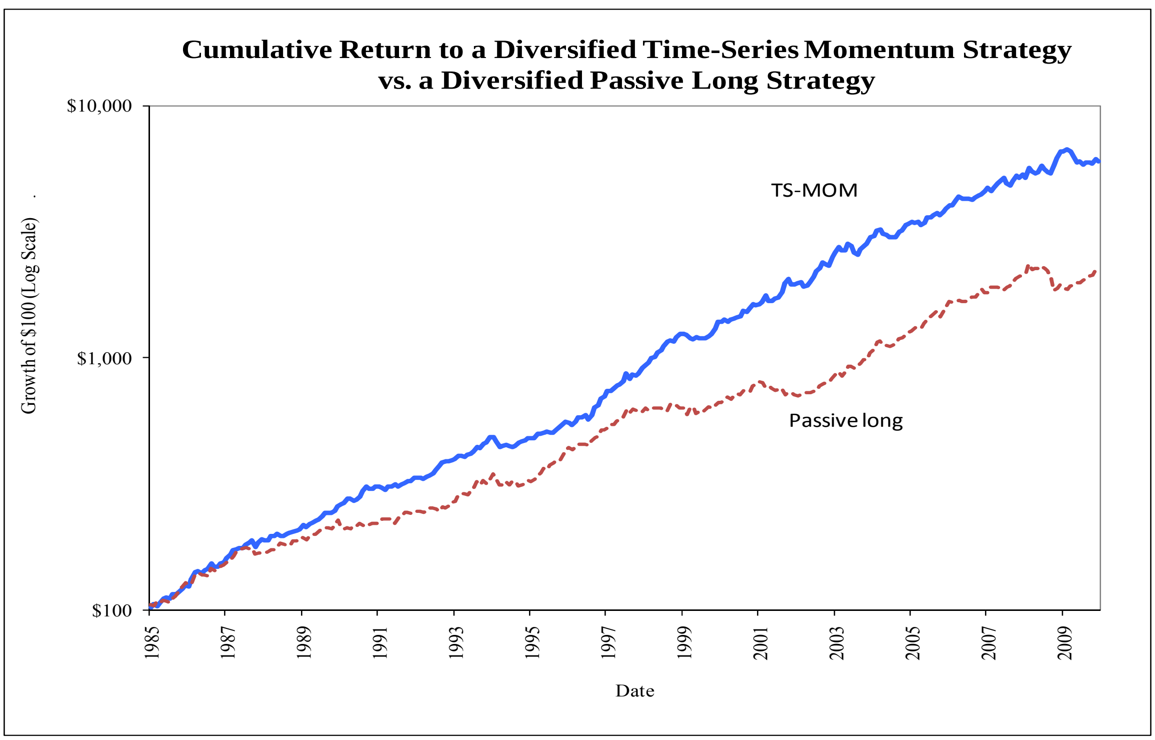


Fig. 5. **Net Speculator Positions**

For each futures contract, the figure plots the average de-meaned Net Speculator Position in, respectively, the sub-sample where the past 12 month returns on the contract are positive ("Positive TS-MOM") and negative ("Negative TS-MOM"). The figure illustrates that speculators are on average positioned to benefit from trends, whereas hedgers, by definition, have the opposite positions.

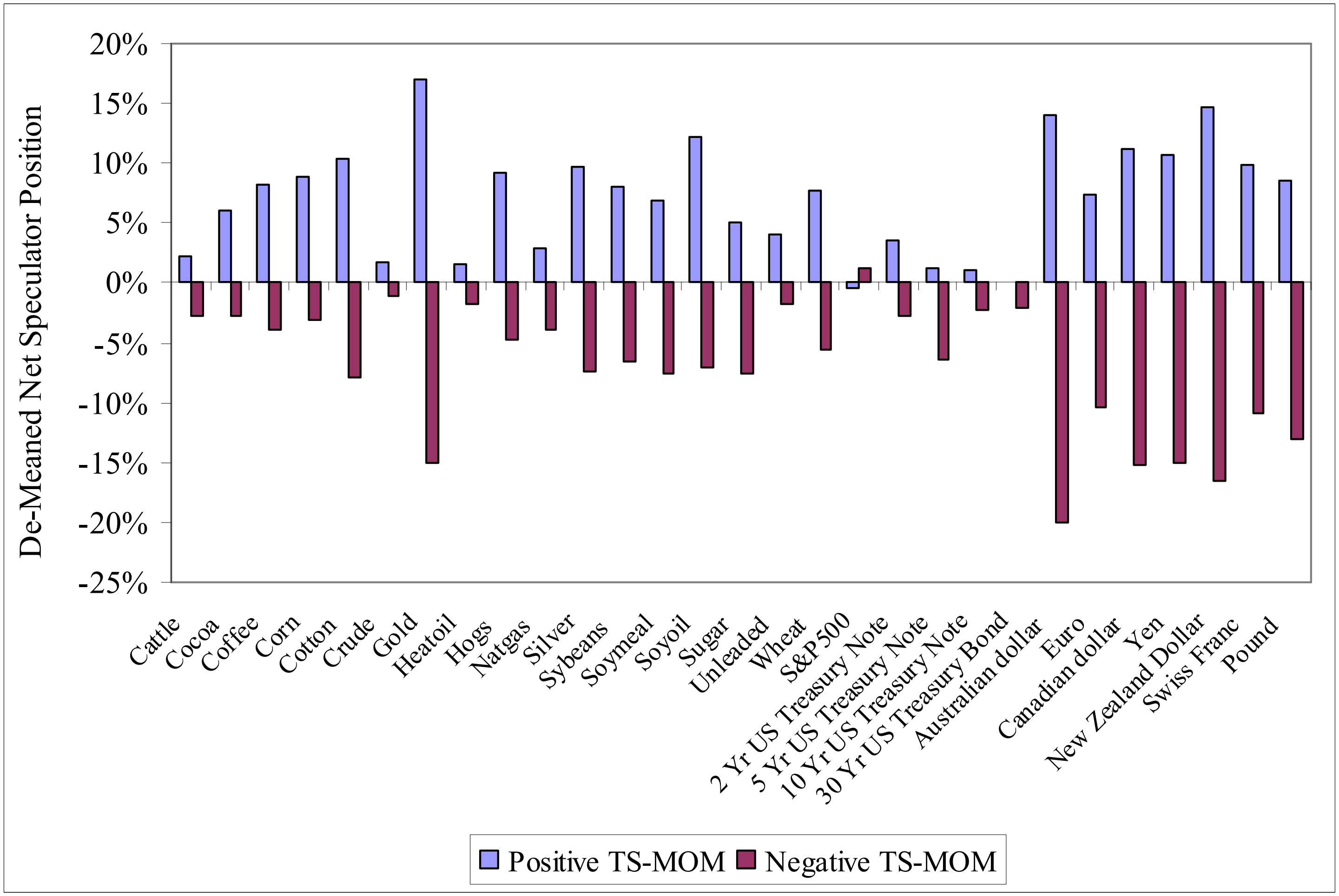
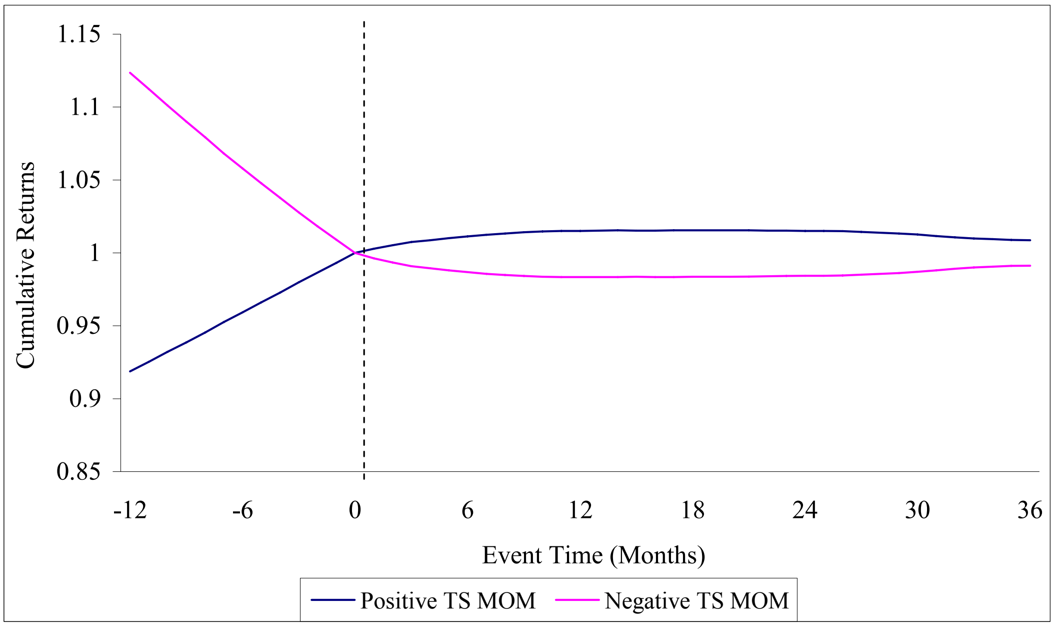


Fig. 6. **Event Study of Time Series Momentum**
For each month and instrument, we identify whether the previous 12 months returns are positive or negative and compute the average return from 12 months prior to the "event date" (portfolio formation date) to 36 months after following positive past year returns ("Positive TS-MOM") and negative past year returns ("Negative TS-MOM"). We standardize the returns to have a zero mean across time and across the two groups (for ease of comparison), and compute the cumulative returns of the subsequent months, where we normalize the cumulative returns to be 1 at the event date. Panel B plots the Net Speculator Position as defined by the CFTC conditional on positive and negative past returns.

Panel A: Cumulative Returns in Event Time



Panel B: Net Speculator Positions in Event Time

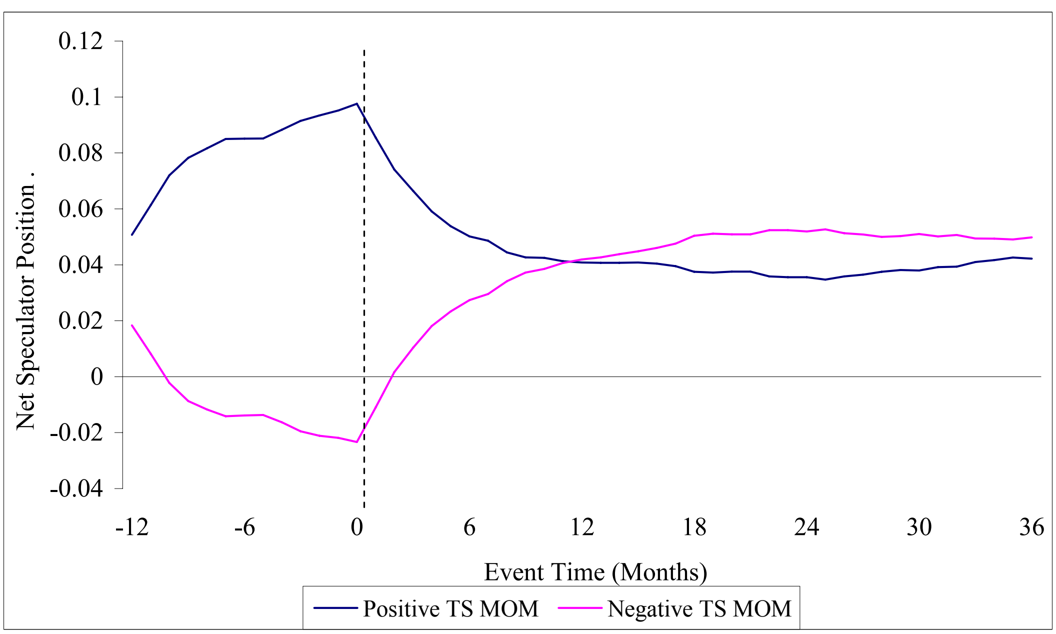
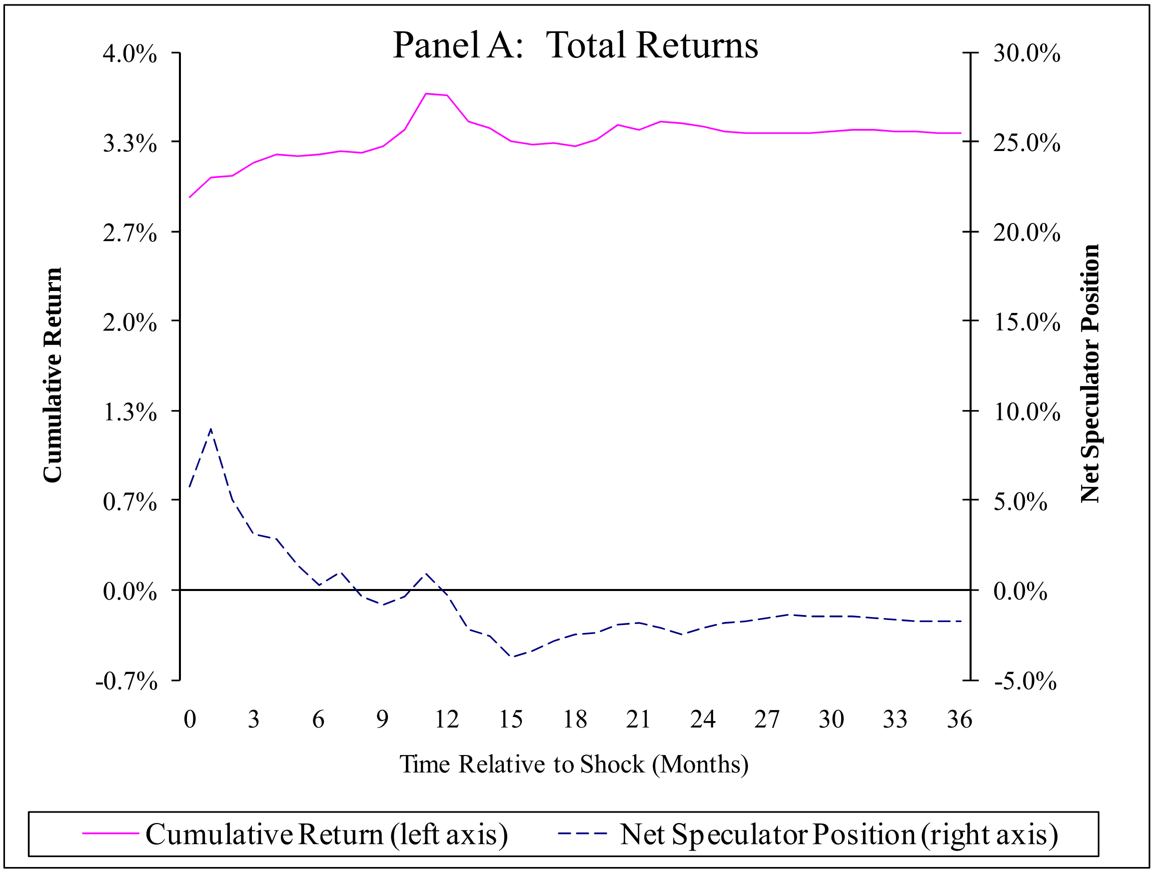
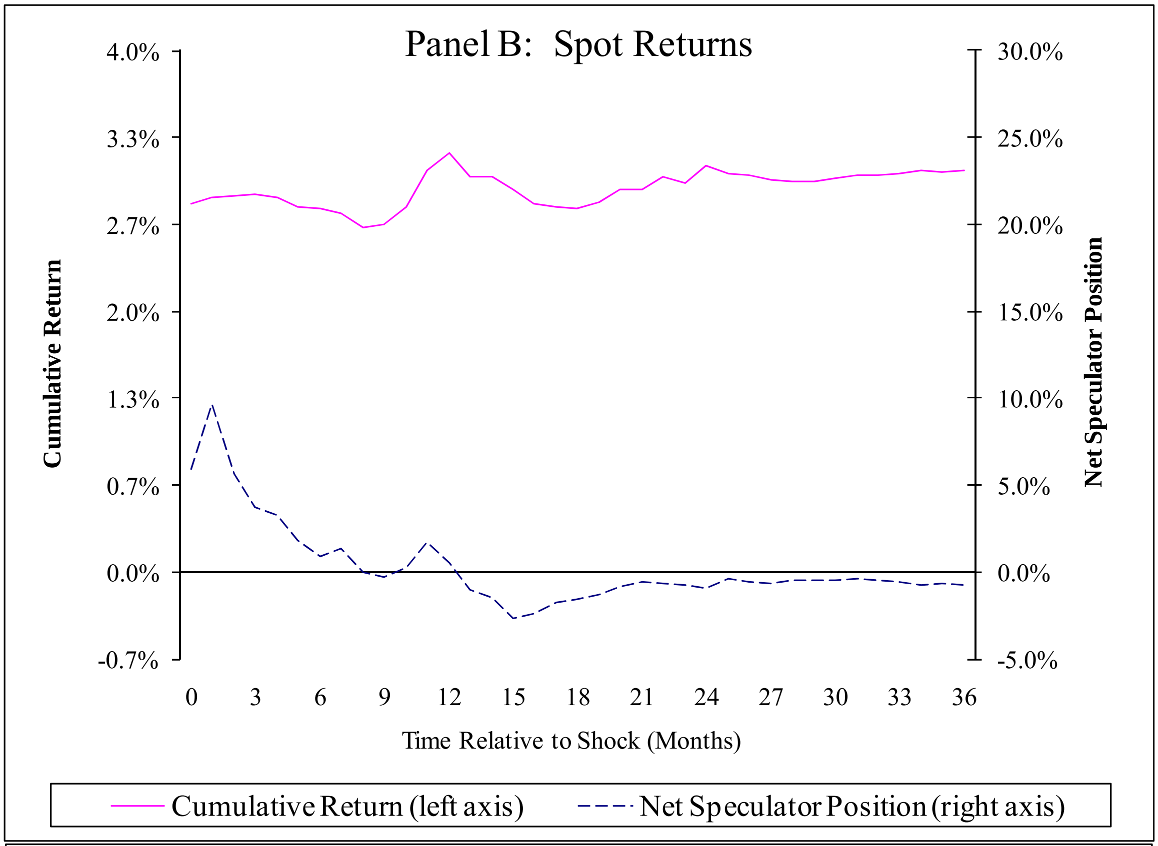


Fig. 7. Impulse Response from a Shock to Returns

Plotted are the cumulative returns and speculators' net positions in response to a one standard deviation shock to total returns on the futures contract (Panel A), returns on the spot asset (Panel B) and returns to rolling the contract (Panel C). The impulse response is based on an estimated vector autoregressive model using monthly returns with 24 lags of returns and net speculator positions that assumes coefficients are the same across all contracts, with a Cholesky decomposition of the shock.




Panel B: Spot Returns
4.0%
3.3%
2.7%
2.0%
1.3%
0.7%
0.0%
-0.7%
Cumulative Return
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
Net Speculator Position
0
3
6
9
12
15
18
21
24
27
30
33
36
Time Relative to Shock (Months)
Cumulative Return (left axis)
Net Speculator Position (right axis)

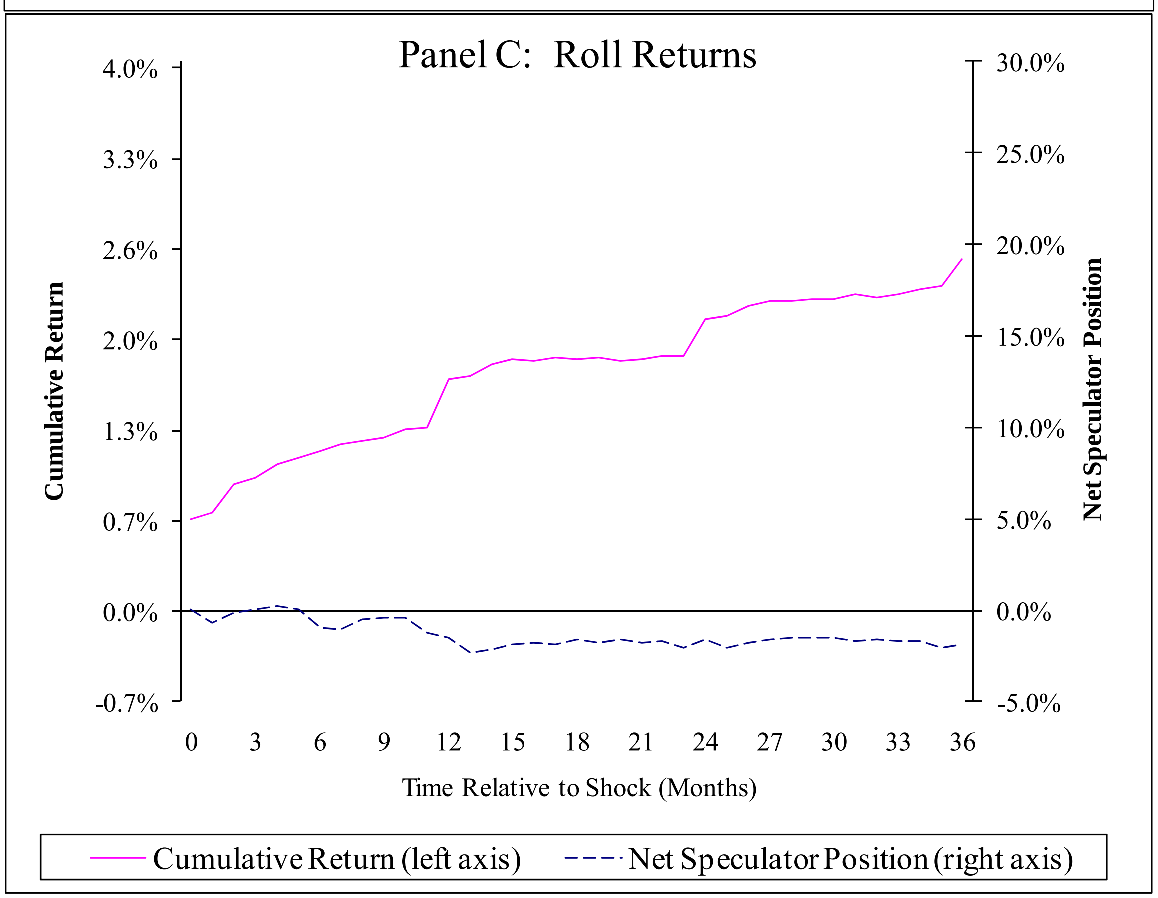

Panel C: Roll Returns
4.0%
3.3%
2.6%
2.0%
1.3%
0.7%
0.0%
-0.7%
Cumulative Return
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
-5.0%
Net Speculator Position
0
3
6
9
12
15
18
21
24
27
30
33
36
Time Relative to Shock (Months)
Cumulative Return (left axis)
Net Speculator Position (right axis)

Table 1. **Summary Statistics on Futures Contracts**

Reported are the annualized mean return and volatility (standard deviation) of the futures contracts in our sample from January 1975 to December 2009 as well as the mean and standard deviation of the net speculator long positions in each contract as a percentage of open interest, covered and defined by the CFTC data, which is available over the period January 1986 to December 2009. For the contracts with CFTC positions data, the table also reports the coefficient and *t*-statistic from a regression of the monthly returns on the futures contract on the previous month's net long speculator positions.

	Data Start Date	Annualized Mean	Annualized Volatility	Average Net Speculator Long Positions	Stdev. Net Speculator Long Positions	Beta of Returns on Lagged Net Speculator Positions	t-stat
Commodity Futures							
ALUMINUM	Jan-79	0.82%	23.6%				
BRENTOIL	Apr-89	13.39%	32.5%				
CATTLE	Jan-65	4.66%	17.2%	8.1%	4.9%	0.17	7.70
COCOA	Jan-65	5.38%	32.4%	4.9%	9.3%	0.17	5.07
COFFEE	Mar-74	6.33%	38.7%	7.5%	11.1%	0.35	7.69
COPPER	Jan-77	8.77%	27.5%				
CORN	Jan-65	-3.42%	24.5%	7.1%	7.0%	0.29	7.99
COTTON	Aug-67	1.56%	24.5%	-0.1%	7.0%	0.17	8.46
CRUDE	Mar-83	11.16%	34.8%	1.0%	10.0%	0.41	3.99
GASOIL	Oct-84	11.69%	33.2%				
GOLD	Dec-69	5.47%	21.4%	6.7%	6.2%	0.07	6.67
HEATOIL	Dec-78	9.52%	33.8%	2.4%	9.8%	0.54	6.35
HOGS	Feb-66	3.54%	26.0%	5.1%	7.5%	0.21	5.52
NATGAS	Apr-90	-10.26%	53.0%	-1.6%	15.4%	0.56	5.30
NICKEL	Jan-93	13.30%	36.1%				
PLATINUM	Jan-92	13.13%	20.9%				
SILVER	Jan-65	3.26%	31.2%	20.6%	9.0%	0.17	5.68
SOYBEANS	Jan-65	5.50%	27.4%	8.2%	7.9%	0.20	6.94
SOYMEAL	Sep-83	6.36%	24.7%	6.7%	7.1%	0.25	7.09
SOYOIL	Oct-90	0.81%	25.4%	5.7%	7.3%	0.22	6.79
SUGAR	Jan-65	3.93%	43.4%	10.0%	12.4%	0.27	7.42
UNLEADED	Dec-84	15.59%	37.3%	7.8%	10.8%	0.21	3.14
WHEAT	Jan-65	-1.41%	25.9%	4.3%	7.2%	0.19	5.96
ZINC	Jan-91	0.78%	25.4%				

	Data Start Date	Annualized Mean	Annualized Volatility	Average Net Speculator Long Positions	Stdev. Net Speculator Long Positions	Beta of Returns on Lagged Net Speculator Positions	t-stat
Equity Index Futures							
ASX SPI 200 (AUS)	Jan-77	6.93%	18.4%				
DAX (GER)	Jan-75	6.38%	20.4%				
IBEX 35 (ESP)	Jan-80	9.01%	22.1%				
CAC 40 10 (FR)	Jan-75	6.55%	20.9%				
FTSE/MIB (IT)	Jun-78	5.89%	24.7%				
TOPIX (JP)	Jul-76	2.13%	18.8%				
AEX (NL)	Jan-75	7.69%	19.2%				
FTSE 100 (UK)	Jan-75	6.91%	17.9%				
S&P 500 (US)	Jan-65	3.45%	15.6%	-4.6%	4.5%	-0.01	-0.23
Bond Futures							
3-year AUS	Jan-92	0.78%	1.5%				
10-year AUS	Dec-85	2.25%	4.9%				
2-year EURO	Mar-97	0.65%	0.9%				
5-year EURO	Jan-93	1.58%	1.8%				
10-year EURO	Dec-79	1.48%	3.3%				
30-year EURO	Dec-98	3.46%	6.7%				
10-year CAN	Dec-84	2.39%	4.2%				
10-year JP	Dec-81	2.11%	3.1%				
10-year UK	Dec-79	1.83%	5.2%				
2-year US	Apr-96	0.99%	1.1%	1.9%	1.1%	0.00	0.45
5-year US	Jan-90	1.94%	2.4%	3.0%	1.2%	0.03	2.94
10-year US	Dec-79	2.33%	5.3%	0.4%	1.5%	0.02	2.17
30-year US	Jan-90	5.97%	10.6%	-1.4%	1.1%	0.03	2.52
Currency Forwards							
AUD/USD	Mar-72	1.91%	11.0%	12.4%	3.1%	0.06	8.10
EUR/USD	Sep-71	1.30%	11.3%	12.1%	3.2%	0.07	5.70
CAD/USD	Mar-72	0.64%	6.4%	4.7%	1.9%	0.04	8.07
JPY/USD	Sep-71	1.51%	11.7%	-6.0%	3.5%	0.07	9.03
NOK/USD	Feb-78	1.24%	10.7%				
NZD/USD	Feb-78	2.30%	12.1%	38.8%	3.3%	0.07	3.62
SEK/USD	Feb-78	-0.09%	11.2%				
CHF/USD	Sep-71	1.29%	12.4%	-5.2%	3.6%	0.06	9.01
GBP/USD	Sep-71	1.30%	10.4%	2.7%	3.1%	0.04	6.90

Table 2. **T-stat of the Alpha of Time Series Momentum Trend Strategies with Different Look-Back and Holding Periods**

Reported are the *t*-statistics of the alphas (intercepts) from time series regressions of the returns of time series momentum or trend strategies over various look-back and holding periods on the following factor portfolios: MSCI World equity market index, Lehman Brothers bond market index, Goldman Sachs Commodity Index, and HML, SMB, and UMD Fama and French factors from Ken French's website. Panel A reports results for all asset classes, Panel B for commodity futures, Panel C for equity index futures, Panel D for bond futures, and Panel E for currency forwards.

		Holding Period (Months)							
		1	3	6	9	12	24	36	48
		Panel A: All Assets							
Lookback Period (Months)	**1**	4.34	4.68	3.83	4.29	5.12	3.02	2.74	1.90
	3	5.35	4.42	3.54	4.73	4.50	2.60	1.97	1.52
	6	5.03	4.54	4.93	5.32	4.43	2.79	1.89	1.42
	9	6.06	6.13	5.78	5.07	4.10	2.57	1.45	1.19
	12	6.61	5.60	4.44	3.69	2.85	1.68	0.66	0.46
	24	3.95	3.19	2.44	1.95	1.50	0.20	-0.09	-0.33
	36	2.70	2.20	1.44	0.96	0.62	0.28	0.07	0.20
	48	1.84	1.55	1.16	1.00	0.86	0.38	0.46	0.74
		Panel B: Commodity Futures							
Lookback Period (Months)	**1**	2.44	2.89	2.81	2.16	3.26	1.81	1.56	1.94
	3	4.54	3.79	3.20	3.12	3.29	1.51	1.28	1.62
	6	3.86	3.53	3.34	3.43	2.74	1.59	1.25	1.48
	9	3.77	4.05	3.89	3.06	2.31	1.27	0.71	1.04
	12	4.66	4.08	2.64	1.85	1.46	0.58	0.14	0.57
	24	2.83	2.15	1.24	0.58	0.18	-0.60	-0.33	-0.14
	36	1.28	0.74	0.07	-0.25	-0.34	-0.03	0.34	0.65
	48	1.19	1.17	1.04	1.01	0.92	0.75	1.16	1.29
		Panel C: Equity Index Futures							
Lookback Period (Months)	**1**	1.05	2.36	2.89	3.08	3.24	2.28	1.93	1.28
	3	1.48	2.23	2.21	2.81	2.78	2.00	1.57	1.14
	6	3.50	3.18	3.49	3.52	3.03	2.08	1.36	0.88
	9	4.21	3.94	3.79	3.30	2.64	1.96	1.21	0.75
	12	3.77	3.55	3.03	2.58	2.02	1.57	0.78	0.33
	24	2.04	2.22	1.96	1.70	1.49	0.87	0.43	0.13
	36	1.86	1.66	1.26	0.90	0.66	0.34	0.02	0.08
	48	0.81	0.84	0.58	0.44	0.36	0.12	0.01	0.23
		Panel D: Bond Futures							
Lookback Period (Months)	**1**	3.31	2.66	1.84	2.65	2.88	1.76	1.60	1.40
	3	2.45	1.52	1.10	1.99	1.80	1.27	1.05	1.00
	6	2.16	2.04	2.18	2.53	2.24	1.71	1.36	1.37
	9	2.93	2.61	2.68	2.55	2.43	1.83	1.17	1.40
	12	3.53	2.82	2.57	2.42	2.18	1.47	1.12	0.96
	24	1.87	1.55	1.62	1.66	1.58	1.01	0.90	0.64
	36	1.97	1.83	1.70	1.62	1.73	1.13	0.75	0.91
	48	2.21	1.80	1.53	1.43	1.26	0.72	0.73	1.22
		Panel E: Currency Forwards							
Lookback Period (Months)	**1**	3.16	3.20	1.46	2.43	2.77	1.22	0.83	-0.42
	3	3.90	2.75	1.54	3.05	2.55	1.02	0.10	-0.84
	6	2.59	1.86	2.32	2.82	2.08	0.62	-0.16	-1.14
	9	3.40	3.16	2.65	2.35	1.72	0.20	-0.38	-1.17
	12	3.41	2.40	1.65	1.25	0.71	-0.29	-1.01	-1.67
	24	1.78	0.99	0.53	0.27	-0.05	-1.15	-1.88	-2.27
	36	0.73	0.42	-0.04	-0.42	-0.96	-1.67	-2.04	-2.42
	48	-0.55	-1.05	-1.41	-1.62	-1.79	-2.02	-2.34	-2.32

Table 3. **Performance of the Diversified Time Series Momentum Strategy**

Panel A reports results from time series regressions of monthly and non-overlapping quarterly returns on the diversified time series momentum strategy, that takes an equal weighted average of the time series momentum strategies across all futures contracts in all asset classes, on the returns of the MSCI World stock market index and the Fama and French factors SMB, HML, and UMD, representing the size, value, and cross-sectional momentum premia in U.S. stocks. Panel B reports results using the Asness, Moskowitz, and Pedersen (2010) Value and Momentum Everywhere factors instead of the Fama and French factors, which capture the premia to value and momentum globally across asset classes. Panel C reports results from regressions of the time series momentum returns on the market, volatility, funding liquidity, and sentiment indicators and their extremes.

Panel A: Fama and French Factors

		MSCI World	SMB	HML	UMD	Intercept	R^2
Monthly	Coefficient	0.03	-0.04	-0.01	0.22	1.26%	16%
	(t-stat)	(1.00)	(-0.92)	(-0.23)	(7.15)	(8.55)	
Quarterly	Coefficient	0.02	-0.14	-0.01	0.25	3.80%	25%
	(t-stat)	(0.29)	(-1.48)	(-0.07)	(4.49)	(8.15)	

Panel B: Asness, Moskowitz, and Pedersen (2010) Factors

		MSCI World		VAL Everywhere	MOM Everywhere	Intercept	R^2
Monthly	Coefficient	0.05		0.06	0.48	0.94%	30%
	(t-stat)	(1.53)		(1.22)	(9.41)	(6.28)	
Quarterly	Coefficient	0.05		0.12	0.50	2.65%	33%
	(t-stat)	(0.94)		(1.53)	(6.13)	(5.00)	

Panel C: Market, Volatility, Liquidity, and Sentiment Extremes

		MSCI World	MSCI World Squared	TED Spread	TED Spread Top 20%	VIX	VIX Top 20%
Quarterly	Coefficient	-0.05	1.45				
	(t-stat)	(-0.91)	(3.68)				
Quarterly	Coefficient			-0.005	-0.005		
	(t-stat)			(-0.25)	(-0.22)		
Quarterly	Coefficient					0.001	-0.005
	(t-stat)					(1.16)	(-0.20)
		Sentiment	**Sentiment Top 20%**	**Sentiment Bottom 20%**	**Change in Sentiment**	**Change in Sentiment Top 20%**	**Change in Sentiment Bottom 20%**
Quarterly	Coefficient	0.03	-0.01	-0.02			
	(t-stat)	(1.00)	(-0.56)	(-0.46)			
Quarterly	Coefficient				-0.01	0.02	0.01
	(t-stat)				(-1.50)	(1.61)	(0.89)

Table 4. **Correlations of Time Series Momentum Strategy Returns Within and Across Asset Classes**

Panel A reports for each asset class the average pair-wise correlation of each instruments' 12-month time series momentum strategy returns, as well as a passive long position in each instrument, *within* the asset class. Panel B reports the correlation of time series momentum strategies (below the diagonal) and passive long positions (above the diagonal) *across* asset classes, where an equal weighted average of the instruments within each asset class is first formed and then the correlations between the equal weighted portfolios across asset classes are calculated. Correlations are calculated from monthly returns over the period January 1985 to December 2009.

Panel A: Average Pair-Wise Correlation Within Asset Class

	Commodities	Equities	Fixed Income	Currencies
TS-MOM strategies	0.07	0.37	0.38	0.10
Passive long positions	0.19	0.60	0.63	-0.04

Panel B: Average Correlation Across Asset Classes

	Correlations of TS-MOM strategies			
Commodities	1			
Equities	**0.18**	1		
Fixed Income	**0.08**	**0.19**	1	
Currencies	**0.16**	**0.20**	**0.10**	1
	Correlations of passive long positions			
Commodities	1			
Equities	**0.17**	1		
Fixed Income	**-0.12**	**-0.03**	1	
Currencies	**-0.12**	**-0.20**	**0.02**	1

Table 5. **Time series Momentum vs. Cross-Sectional Momentum**

Panel A reports results from regressions of the 12-month time series momentum strategies by asset class (TS-MOM) on 12-month cross-sectional momentum strategies (XS-MOM) of Asness, Moskowitz, and Pedersen (2010). Panel B reports results from the decomposition of cross-sectional momentum and time series momentum strategies according to Section 4.B., where Auto is the component of profits coming from the auto-covariance of returns, Cross is the component coming from cross-serial correlations or lead-lag effects across the asset returns, Mean is the component coming from cross-sectional variation in unconditional mean returns, and Mean squared is the component coming from squared mean returns.

Panel A: Regression of TS-MOM on XS-MOM

		Independent Variables							
		XS-MOM ALL	**XS-MOM COM**	**XS-MOM EQ**	**XS-MOM FI**	**XS-MOM FX**	**XS-MOM US Stocks**	**Intercept**	R^2
Dependent Variable	TS-MOM ALL	0.57						0.66%	45%
		(15.52)						(5.64)	
	TS-MOM ALL		0.62	0.43	0.34	0.71	0.34	0.64%	48%
			(7.00)	(4.67)	(3.74)	(8.23)	(3.26)	(5.50)	
	TS-MOM COM		0.61					0.23%	41%
			(14.29)					(3.99)	
	TS-MOM COM		0.58	0.05	0.02	0.13	0.08	0.20%	44%
			(13.48)	(1.07)	(0.53)	(3.16)	(1.52)	(3.50)	
	TS-MOM EQ			0.32				0.18%	15%
				(7.33)				(2.95)	
	TS-MOM EQ		0.06	0.23	0.03	0.05	0.22	0.16%	22%
			(1.29)	(5.09)	(0.64)	(1.11)	(4.28)	(2.74)	
	TS-MOM FI				0.32			0.20%	12%
					(6.48)			(3.24)	
	TS-MOM FI		-0.05	0.13	0.29	0.02	0.05	0.17%	15%
			(-0.96)	(2.54)	(5.83)	(0.53)	(0.89)	(2.72)	
	TS-MOM FX					0.51		0.13%	60%
						(21.18)		(3.98)	
	TS-MOM FX		0.03	0.01	0.00	0.51	-0.01	0.13%	60%
			(0.99)	(0.51)	(-0.15)	(20.41)	(-0.35)	(3.64)	

Panel B: Decomposition of TS-MOM and XS-MOM							
	XS-MOM Decomposition				TS-MOM Decomposition		
	Auto	Cross	Mean	Total	Auto	Mean Squared	Total
ALL	0.53%	-0.03%	0.12%	0.61%	0.54%	0.29%	0.83%
COM	0.41%	-0.13%	0.11%	0.39%	0.43%	0.17%	0.59%
EQ	0.74%	-0.62%	0.02%	0.14%	0.83%	0.17%	1.00%
FI	0.32%	-0.10%	0.05%	0.27%	0.35%	0.70%	1.05%
FX	0.71%	-0.55%	0.02%	0.18%	0.80%	0.17%	0.96%

Table 6. **Time Series Predictors of Returns: Spot Prices, Roll Returns, and Positions**

Reported are results from regressions of the monthly futures return on the previous 12 months futures return ("Full TS Mom"), previous 12 months change in spot price ("Spot Price Mom"), past 12-month roll return ("Roll Mom"), and the 12-month change in speculators' aggregate net (i.e., long minus short) positions as a percent of open interest ("Chg Net Speculator Position"). Also reported are interactions between the change in net speculator positions and the spot and roll returns over the previous 12 months.

	Full TS Mom	**Spot Price Mom**	**Roll Mom**	**Chg Net Speculator Position**	**Spot Mom x Chg Net Spec Pos**	**Roll Mom x Chg Net Spec Pos**	**Intercept**	**R2**
Coefficient	0.019						0.09%	0.6%
T-stat	(3.54)						(1.31)	
Coefficient		0.014					0.12%	0.3%
T-stat		(2.27)					(1.72)	
Coefficient			0.024				0.08%	0.3%
T-stat			(3.22)				(1.09)	
Coefficient				0.007			0.12%	0.2%
T-stat				(2.66)			(1.64)	
Coefficient	0.017			0.004			0.10%	0.7%
T-stat	(3.10)			(1.65)			(1.34)	
Coefficient		0.017	0.030				0.08%	0.6%
T-stat		(2.72)	(3.90)				(1.03)	
Coefficient		0.014	0.030	0.005			0.07%	0.8%
T-stat		(2.10)	(3.93)	(1.89)			(0.99)	
Coefficient		0.014	0.030	0.005	0.024	0.016	0.06%	0.8%
T-stat		(2.16)	(3.93)	(1.77)	(1.44)	(0.54)	(0.77)	