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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 one 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. Examining the trading activities of speculators and hedgers, we find that speculators profit from time series momentum at the expense of hedgers.

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 almost five dozen diverse futures and forward contracts that include country equity indexes, 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 subsamples, look-back periods, and holding periods. We find that 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 finance literature, which is primarily 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 three to 12 months continue to outperform their

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peers on average over the next month.[1] Rather than focus on the relative returns of securities in the cross-section, time series momentum focuses purely on a security's *own* past return.

We argue that 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, therefore having direct implications for time series, rather than cross-sectional, predictability. Likewise, rational theories of momentum (Berk, Green, and Naik, 1999; Johnson, 2002; Ahn, Conrad, and Dittmar, 2003; Liu and Zhang, 2008; Sagi and Seasholes, 2007) also pertain to a single risky asset.

Our finding of positive time series momentum 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.[2] However, our results 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, we fail to find a link between time series momentum and measures of investor sentiment used in the literature (Baker and Wurgler, 2006; Qiu and Welch, 2006).

To understand the relationship between time series and cross-sectional momentum, their underlying drivers, and relation to theory, we decompose the returns to a time series and cross-sectional momentum strategy following the framework of Lo and Mackinlay (1990) and Lewellen (2002). This decomposition allows us to identify the properties of returns that contribute to these patterns, and what features are common and unique to the two strategies. We find that positive auto-covariance in 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. In fact, negative serial cross-correlations (i.e., lead-lag effects across securities), which affect cross-sectional momentum, are negligible and of the "wrong" sign among our instruments to explain time series momentum. Our finding that time series and cross-sectional momentum profits arise due to auto-covariances is consistent with the theories mentioned above.[3] In addition, we find that time series momentum captures the returns associated with individual stock (cross-sectional) momentum, most notably Fama and French's UMD factor, despite time series momentum being constructed from a completely different set of securities. This finding indicates strong correlation structure between time series momentum and cross-sectional momentum even when applied to different assets and suggests that our time series momentum portfolio captures individual stock momentum.

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 reducing their positions when the trend begins to reverse. Consequently, speculators appear to be profiting from time series momentum at the expense of hedgers. Using a vector auto-regression (VAR), we confirm 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.

Finally, 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. 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

[1] Cross-sectional momentum has been documented in US equities (Jegadeesh and Titman, 1993; Asness, 1994), other equity markets (Rouwenhorst, 1998), industries (Moskowitz and Grinblatt, 1999), equity indexes (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, 2010). Garleanu and Pedersen (2009) show how to trade optimally on momentum and reversal in light of transaction costs, and DeMiguel, Nogales, and Uppal (2010) show how to construct an optimal portfolio based on stocks' serial dependence and find outperformance out-of-sample. Our study is related to but different from Asness, Moskowitz, and Pedersen (2010) who study cross-sectional momentum and value strategies across several asset classes including individual stocks. We complement their study by examining time series momentum and its relation to cross-sectional momentum and hedging pressure in some of the same asset classes.

[2] Under-reaction 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 hold on to 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).

[3] However, this result differs from Lewellen's (2002) finding for equity portfolio returns that temporal 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 of the Lewellen (2002) portfolios that is consistent with auto-covariance being the primary driver of stock momentum.

only spot price changes are associated with long-term reversals, consistent with the idea that investors may be over-reacting to information in the spot market but that hedging pressure is more long-lived and not affected by over-reaction.

Our finding of time series momentum in virtually every instrument we examine seems to challenge the "random walk" hypothesis, which in its most basic form 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. 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 premiums, we further show that a diversified portfolio of time series momentum across all assets is remarkably stable and robust, yielding a Sharpe ratio greater than one on an annual basis, or roughly 2.5 times the Sharpe ratio for the equity market portfolio, with little correlation to passive benchmarks in each asset class or a host of standard asset pricing factors. The abnormal returns to time series momentum also do not appear to be compensation for crash risk or tail events. Rather, the return to time series momentum tends 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 suggest that our results are not likely spurious, and the relatively short duration of the predictability (less than a year) and the magnitude of the return premium associated with time series momentum present significant challenges to the random walk hypothesis and perhaps also to the efficient market hypothesis, though we cannot rule out the existence of a rational theory that can explain these findings.

Our study relates to the literature on return autocorrelation and variance ratios that also finds deviations from the random walk hypothesis (Fama and French, 1988; Lo and Mackinlay, 1988; Poterba and Summers, 1988). While this literature is largely focused on US and global equities, Cutler, Poterba, and Summers (1991) study a variety of assets including housing and collectibles. The literature finds positive return autocorrelations at daily, weekly, and monthly horizons and negative autocorrelations at annual and multi-year frequencies. We complement this literature in several ways. The studies of autocorrelation examine, by definition, 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 *one month* is missed by looking at one-year autocorrelations. While return continuation can also be detected implicitly from variance ratios, we complement the literature by explicitly documenting the extent of return continuation and by constructing a time series momentum factor that can help explain existing asset pricing phenomena, such as cross-sectional momentum premiums and hedge fund macro and managed futures returns. Also, a significant component of the higher frequency findings in equities is contaminated by market microstructure 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 mitigates many of these issues. Finally, unique to this literature, we link time series predictability to the dynamics of hedger and speculator positions and decompose returns into price changes and roll yields.

Our paper is also related to the literature on hedging pressure in commodity futures (Keynes, 1923; Fama and French, 1987; Bessembinder, 1992; de Roon, Nijman, and Veld, 2000). We complement this literature by showing how hedger and speculator positions relate to past futures returns (and not just in commodities), finding that speculators' positions load positively on time series momentum, while hedger positions load negatively on it. Also, we consider the relative return predictability of positions, past price changes, and past roll yields. Gorton, Hayashi, and Rouwenhorst (2008) also link commodity momentum and speculator positions to the commodities' inventories.

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 horizons less than a year and reversals beyond that. Section 4 defines a time series momentum factor, studying its relation to other known return factors, its performance during extreme markets, and correlations within and across asset classes. Section 5 examines the relation between time series and cross-sectional momentum, showing how time series momentum is a central driver of cross-sectional momentum as well as macro and managed futures hedge fund returns. Section 6 studies the evolution of time series momentum and its relation to investor speculative and hedging positions. Section 7 concludes.

2. Data and preliminaries

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

2.1. Futures returns

Our data consist of futures prices for 24 commodities, 12 cross-currency pairs (from nine underlying currencies), nine developed equity indexes, and 13 developed government bond futures, from January 1965 through December 2009. These instruments are among the most liquid futures contracts in the world.[4] We focus on the most liquid instruments to avoid returns being contaminated by illiquidity or stale price issues and to match more

[4] We also confirm the time series momentum returns are robust among more illiquid instruments such as illiquid commodities (feeder cattle, Kansas wheat, lumber, orange juice, rubber, tin), emerging market currencies and equities, and more illiquid fixed income futures (not reported).

closely an implementable strategy at a significant trade size. Appendix A provides details on each instrument and their data sources, which are mainly Datastream, Bloomberg, and various exchanges.

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 cumulative return index from which we can compute returns at any horizon. For the equity indexes, our return series are almost perfectly correlated with the corresponding returns of the underlying cash indexes in excess of the Treasury bill rate.[5]

As a robustness test, we also use the "far" futures contract (the next maturity after the most liquid one). For the commodity futures, time series momentum profits are in fact slightly stronger for the far contract, and, for the financial futures, time series momentum returns hardly change if we use far futures.

Table 1 presents summary statistics of the excess returns on our futures contracts. The first column reports when the time series of returns for each asset starts, and the next two columns report the time series mean (arithmetic) and standard deviation (annualized) of each contract by asset class: commodities, equity indexes, 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 commodities, there is substantial cross-sectional variation in volatilities. Making comparisons across instruments with vastly different volatilities or combining various instruments into a diversified portfolio when they have wide-ranging volatilities is challenging. 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.

2.2. Positions of traders

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; de Roon, Nijman, and Veld, 2000), refer to as hedgers and speculators, respectively. For each futures contract, the long and short open interest held by these traders on Tuesday are reported on a weekly basis.[6]

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

$$\text{Net speculator position} = \frac{\text{Speculator long positions} - \text{Speculator short positions}}{\text{Open interest}}.$$

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 do 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 US 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 two of the commodities (natural gas and cotton) have net long speculator positions over the sample period, with silver exhibiting the largest average net long speculator position. This is consistent with Keynes' (1923) conjecture that producers of commodities are the primary hedgers in markets and are on the short side of these contracts as a result. For the other asset classes, other than the S&P 500, the 30-year US 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.

2.3. Asset pricing benchmarks

We evaluate the returns of our strategies relative to standard asset pricing benchmarks, namely the MSCI World equity index, Barclay's Aggregate Bond Index, S&P GSCI Index, all of which we obtain from Datastream, the long-short factors *SMB*, *HML*, and *UMD* from Ken French's Web site, and the long-short value and cross-sectional

[5] Bessembinder (1992) and de Roon, Nijman, and Veld (2000) compute returns on futures contracts similarly and also find that futures returns are highly correlated with spot returns on the same underlying asset.

[6] 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, the potential attenuation bias associated with such misclassification may only weaken our results.

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 1965 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 are available over the period January 1986 to December 2009. For a detailed description of our sample of futures contracts, see Appendix A.

	Data start date	Annualized mean	Annualized volatility	Average net speculator long positions	Std. dev. net speculator long positions
Commodity futures					
ALUMINUM	Jan-79	0.97%	23.50%		
BRENTOIL	Apr-89	13.87%	32.51%		
CATTLE	Jan-65	4.52%	17.14%	8.1%	9.6%
COCOA	Jan-65	5.61%	32.38%	4.9%	14.0%
COFFEE	Mar-74	5.72%	38.62%	7.5%	13.6%
COPPER	Jan-77	8.90%	27.39%		
CORN	Jan-65	−3.19%	24.37%	7.1%	11.0%
COTTON	Aug-67	1.41%	24.35%	−0.1%	19.4%
CRUDE	Mar-83	11.61%	34.72%	1.0%	5.9%
GASOIL	Oct-84	11.95%	33.18%		
GOLD	Dec-69	5.36%	21.37%	6.7%	23.0%
HEATOIL	Dec-78	9.79%	33.78%	2.4%	6.4%
HOGS	Feb-66	3.39%	26.01%	5.1%	14.5%
NATGAS	Apr-90	−9.74%	53.30%	−1.6%	8.9%
NICKEL	Jan-93	12.69%	35.76%		
PLATINUM	Jan-92	13.15%	20.95%		
SILVER	Jan-65	3.17%	31.11%	20.6%	14.3%
SOYBEANS	Jan-65	5.57%	27.26%	8.2%	12.8%
SOYMEAL	Sep-83	6.14%	24.59%	6.7%	11.2%
SOYOIL	Oct-90	1.07%	25.39%	5.7%	12.8%
SUGAR	Jan-65	4.44%	42.87%	10.0%	14.2%
UNLEADED	Dec-84	15.92%	37.36%	7.8%	9.6%
WHEAT	Jan-65	−1.84%	25.11%	4.3%	12.1%
ZINC	Jan-91	1.98%	24.76%		
Equity index futures					
ASX SPI 200 (AUS)	Jan-77	7.25%	18.33%		
DAX (GER)	Jan-75	6.33%	20.41%		
IBEX 35 (ESP)	Jan-80	9.37%	21.84%		
CAC 40 10 (FR)	Jan-75	6.73%	20.87%		
FTSE/MIB (IT)	Jun-78	6.13%	24.59%		
TOPIX (JP)	Jul-76	2.29%	18.66%		
AEX (NL)	Jan-75	7.72%	19.18%		
FTSE 100 (UK)	Jan-75	6.97%	17.77%		
S&P 500 (US)	Jan-65	3.47%	15.45%	−4.6%	5.4%
Bond futures					
3-year AUS	Jan-92	1.34%	2.57%		
10-year AUS	Dec-85	3.83%	8.53%		
2-year EURO	Mar-97	1.02%	1.53%		
5-year EURO	Jan-93	2.56%	3.22%		
10-year EURO	Dec-79	2.40%	5.74%		
30-year EURO	Dec-98	4.71%	11.70%		
10-year CAN	Dec-84	4.04%	7.36%		
10-year JP	Dec-81	3.66%	5.40%		
10-year UK	Dec-79	3.00%	9.12%		
2-year US	Apr-96	1.65%	1.86%	1.9%	11.3%
5-year US	Jan-90	3.17%	4.25%	3.0%	9.2%
10-year US	Dec-79	3.80%	9.30%	0.4%	8.0%
30-year US	Jan-90	9.50%	18.56%	−1.4%	6.2%
Currency forwards					
AUD/USD	Mar-72	1.85%	10.86%	12.4%	28.8%
EUR/USD	Sep-71	1.57%	11.21%	12.1%	18.7%
CAD/USD	Mar-72	0.60%	6.29%	4.7%	24.1%
JPY/USD	Sep-71	1.35%	11.66%	−6.0%	23.8%
NOK/USD	Feb-78	1.37%	10.56%		
NZD/USD	Feb-78	2.31%	12.01%	38.8%	33.8%
SEK/USD	Feb-78	−0.05%	11.06%		
CHF/USD	Sep-71	1.34%	12.33%	−5.2%	26.8%
GBP/USD	Sep-71	1.39%	10.32%	2.7%	25.4%

momentum factors across asset classes from Asness, Moskowitz, and Pedersen (2010).

2.4. 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., similar to a simple univariate GARCH model). Specifically, the ex ante annualized variance σ_t^2 for each instrument is calculated as follows:

$$\sigma_t^2 = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \bar{r}_t)^2, \tag{1}$$

where the scalar 261 scales the variance to be annual, the weights $(1-\delta)\delta^i$ add up to one, and $\bar{r}_t$ is the exponentially weighted average return computed similarly. The parameter δ is chosen so that the center of mass of the weights is $\sum_{i=0}^{\infty}(1-\delta)\delta^i i = \delta/(1-\delta) = 60$ 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: Regression analysis and trading strategies

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

3.1. 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 2.4):

$$r_t^s/\sigma_{t-1}^s = \alpha + \beta_h r_{t-h}^s/\sigma_{t-h-1}^s + \varepsilon_t^s. \tag{2}$$

Given the vast differences in volatilities (as shown in Table 1), we divide all returns by their volatility to put them on the same scale. This is similar to using Generalized Least Squares instead of Ordinary Least Squares (OLS).[7] 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 $h=1, 2, \ldots, 60$ months.

Panel A of Fig. 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:

$$r_t^s/\sigma_{t-1}^s = \alpha + \beta_h \mathit{sign}(r_{t-h}^s) + \varepsilon_t^s. \tag{3}$$

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 Fig. 1.

The results are similar across the two regression specifications: strong return continuation for the first year and weaker reversals for the next 4 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 time series momentum followed by smaller reversals over the next 4 years as seen in Panel C of Fig. 1.

3.2. Time series momentum trading strategies

We next investigate the profitability of a number of trading strategies based on time series momentum. We vary both the number of months we lag returns 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.

For each trading strategy (k,h), we derive a *single* time series of monthly returns even if the holding period h is more than one month. Hence, we do not have overlapping observations. We derive this single time series of returns following the methodology used by Jegadeesh and Titman (1993): The return at time t represents the average return across *all* portfolios at that time, namely 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.

Specifically, for each instrument, we compute the time-t return based on the sign of the past return from

[7] The regression results are qualitatively similar if we run OLS without adjusting for each security's volatility.

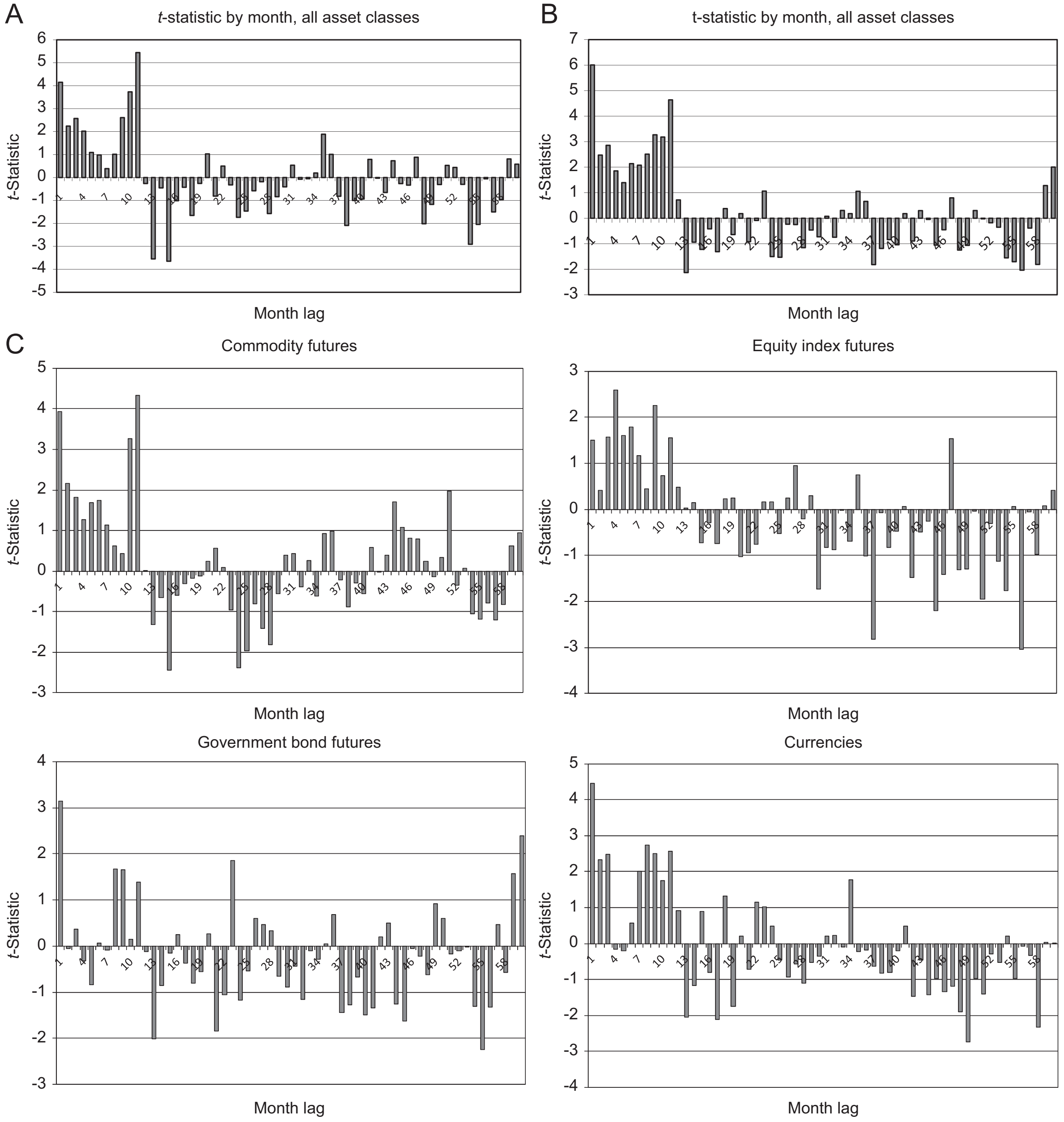

Fig. 1. Time series predictability across all asset classes. We regress the monthly excess return of each contract on its own lagged excess return over various horizons. Panel A uses the size of the lagged excess return as a predictor, where returns are scaled by their ex ante volatility to make them comparable across assets, 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, and Panel C reports the results of the sign regression by asset class. Reported are the pooled regression estimates across all instruments with *t*-statistics computed using standard errors that are clustered by time (month). Sample period is January 1985 to December 2009. (A) *Panel A*: $r_t^s/\sigma_{t-1}^s = \alpha + \beta_h r_{t-h}^s/\sigma_{t-h-1}^s + \varepsilon_t^s$; (B) *Panel B*: $r_t^s/\sigma_{t-1}^s = \alpha + \beta_h sign(r_{t-h}^s) + \varepsilon_t^s$; (C) *Panel C*: Results by asset class.

time $t-k-1$ to $t-1$. We then compute the time-t return based on the sign of the past return from $t-k-2$ to $t-2$, and so on until we compute the time-t return based on the final past return that is still being used from $t-k-h$ to $t-h$. For each (k,h), we get a single time series of monthly returns by computing the average return of all of these h currently "active" portfolios (i.e., the portfolio that was just bought and those that were bought in the past and are still held). We average the returns across all instruments (or all instruments within an asset class), to obtain our time series momentum strategy returns, $r_t^{TSMOM(k,h)}$.

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

$$r_t^{TSMOM(k,h)} = \alpha + \beta_1 MKT_t + \beta_2 BOND_t + \beta_3 GSCI_t + sSMB_t + hHML_t + mUMD_t + \varepsilon_t, \quad (4)$$

where we control for passive exposures to the three major asset classes—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

Table 2
t-statistics of the alphas of time series momentum 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 strategies over various look-back and holding periods on the following factor portfolios: MSCI World Index, Lehman Brothers/Barclays Bond Index, S&P GSCI Index, and HML, SMB, and UMD Fama and French factors from Ken French's Web site. 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

commodity market *GSCI*, proxied by the S&P GSCI Index—as well as the standard Fama-French stock market factors *SMB, HML,* and *UMD* for the size, value, and (cross-sectional) momentum premiums. 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 are included going back to 1965, but given the more limited breadth and liquidity of the instruments during this time, we report results post-1985.

Table 2 shows the *t*-statistics of the estimated alphas for each asset class and across all assets. 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 indexes for the stock index futures. The other asset classes do not have cash indexes.

4. Time series momentum factor

For a more in-depth analysis of time series momentum, we focus our attention on a single time series momentum strategy. Following the convention used in the cross-sectional momentum literature (and based on the results from Fig. 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 TSMOM.

4.1. TSMOM by security and the diversified TSMOM factor

We start by looking at each instrument and asset separately and then pool all the assets together in a diversified TSMOM portfolio. We size each position (long or short) so that it has an ex ante annualized volatility of 40%. That is, the position size is chosen to be $40\%/\sigma_{t-1}$, where σ_{t-1} is the estimate of the ex ante volatility of the contract as described above. The choice of 40% is inconsequential, but it makes it easier to intuitively compare our portfolios to others in the literature. The 40% annual volatility is chosen because it is similar to the risk of an average individual stock, and when we average the return across all securities (equal-weighted) to form the portfolio of securities which represent our TSMOM factor, it has an annualized volatility of 12% per year over the sample period 1985–2009, which is roughly the level of volatility exhibited by other factors such as those of Fama and French (1993) and Asness, Moskowitz, and Pedersen (2010).[8] The TSMOM return for any instrument *s* at time *t* is therefore:

$$r_{t,t+1}^{TSMOM,s} = sign(r_{t-12,t}^{s})\frac{40\%}{\sigma_t^s} r_{t,t+1}^{s}. \qquad (5)$$

We compute this return for each instrument and each available month from January 1985 to December 2009. The top of Fig. 2 plots the annualized Sharpe ratios of these strategies for each futures contract. As the figure shows, *every* single futures contract exhibits positive predictability from past one-year returns. All 58 futures contracts exhibit positive time series momentum returns and 52 are statistically different from zero at the 5% significance level.

If we regress the TSMOM strategy for each security on the strategy of always being long (i.e., replacing "sign" with a 1 in Eq. (5)), then we get a positive alpha in 90% of the cases (of which 26% are statistically significant; none of the few negative ones are significant). Thus, a time series momentum strategy provides additional returns over and above a passive long position for most instruments.

The overall return of the strategy that diversifies across all the S_t securities that are available at time *t* is

$$r_{t,t+1}^{TSMOM} = \frac{1}{S_t}\sum_{s=1}^{S_t} sign(r_{t-12,t}^{s})\frac{40\%}{\sigma_t^s} r_{t,t+1}^{s}.$$

We analyze the risk and return of this factor in detail next. We also consider TSMOM strategies by asset class constructed analogously.

4.2. Alpha and loadings on risk factors

Table 3 examines the risk-adjusted performance of a diversified TSMOM strategy and its factor exposures. Panel A of Table 3 regresses the excess return of the TSMOM 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, TSMOM delivers a large and significant alpha or intercept with respect to these factors of about 1.58% per month or 4.75% per quarter. The TSMOM 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 portfolios 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 value everywhere factor, but significant loading on the cross-sectional

[8] Also, this portfolio construction implies a use of margin capital of about 5–20%, which is well within what is feasible to implement in a real-world portfolio.

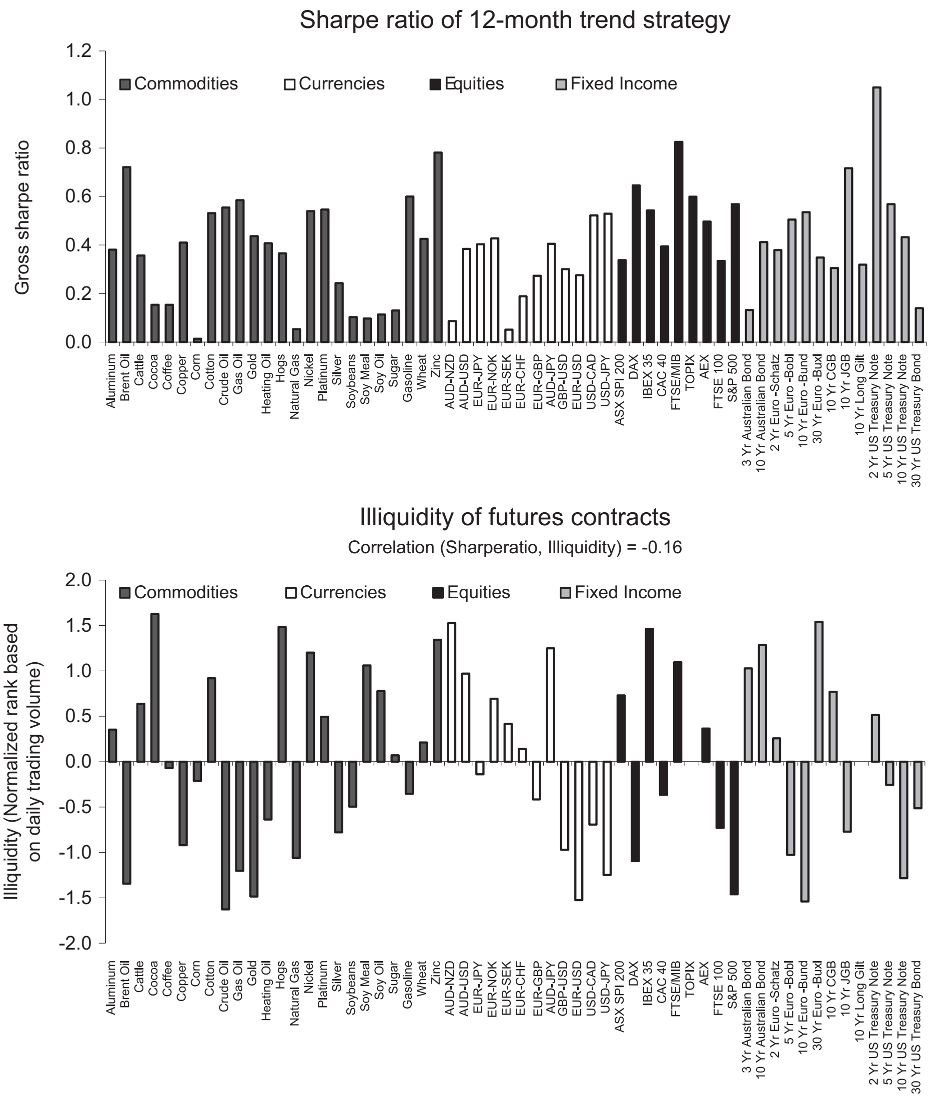

Fig. 2. Sharpe ratio of 12-month time series momentum by instrument. Reported are the annualized gross Sharpe ratio of the 12-month time series momentum or trend strategy for each futures contract/instrument. For each instrument in every month, the trend strategy goes long (short) the contract if the 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.

momentum everywhere factor. However, the returns to TSMOM are not fully captured by the cross-sectional everywhere factor—the alpha is still an impressive 1.09% per month with a *t*-stat of 5.40 or 2.93% per quarter with a *t*-stat of 4.12.

4.3. Performance over time and in extreme markets

Fig. 3 plots the cumulative excess return to the diversified time series momentum strategy over time (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 have the same ex ante volatility except for differences in correlations among time series momentum strategies and passive long strategies.) As Fig. 3 shows, the performance over time of the diversified time series momentum strategy provides a relatively steady stream of positive returns that outperforms a diversified portfolio of passive long positions in all futures contracts (at the same ex ante volatility).

We can also compute the return of the time series momentum factor from 1966 to 1985, despite the limited number of instruments with available data. Over this earlier sample, time series momentum has a statistically

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 Index and the Fama and French factors SMB, HML, and UMD, representing the size, value, and cross-sectional momentum premiums in US 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 premiums to value and cross-sectional momentum globally across asset classes. Panel C reports results from regressions of the time series momentum returns on the market (MSCI World Index), volatility (VIX), funding liquidity (TED spread), and sentiment variables from Baker and Wurgler (2006, 2007), as well as their extremes.

Panel A: Fama and French factors

		MSCI World	SMB	HML	UMD	Intercept	R^2
Monthly	Coefficient	0.09	−0.05	−0.01	0.28	1.58%	14%
	(t-Stat)	(1.89)	(−0.84)	(−0.21)	(6.78)	(7.99)	
Quarterly	Coefficient	0.07	−0.18	0.01	0.32	4.75%	23%
	(t-Stat)	(1.00)	(−1.44)	(0.11)	(4.44)	(7.73)	

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

		MSCI World		VAL Everywhere	MOM Everywhere	Intercept	R^2
Monthly	Coefficient	0.11		0.14	0.66	1.09%	30%
	(t-Stat)	(2.67)		(2.02)	(9.74)	(5.40)	
Quarterly	Coefficient	0.12		0.26	0.71	2.93%	34%
	(t-Stat)	(1.81)		(2.45)	(6.47)	(4.12)	

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	−0.01	1.99				
	(t-Stat)	(−0.17)	(3.88)				
Quarterly	Coefficient			−0.001	−0.008		
	(t-Stat)			(−0.06)	(−0.29)		
Quarterly	Coefficient					0.001	−0.003
	(t-Stat)					(0.92)	(−0.10)
		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	−0.01			
	(t-Stat)	(0.73)	(−0.27)	(−0.12)			
Quarterly	Coefficient				−0.01	0.02	0.01
	(t-Stat)				(−1.08)	(1.25)	(0.66)

significant return and an annualized Sharpe ratio of 1.1, providing strong out-of-sample evidence of time series momentum.[9]

Fig. 3 highlights that time series momentum profits are large in October, November, and December of 2008, which was at the height of the Global Financial Crisis when commodity and equity prices dropped sharply, bond prices rose, and currency rates moved dramatically. Leading into this period, time series momentum suffers losses in the third quarter of 2008, where the associated price moves caused the TSMOM strategy to be short in many contracts, setting up large profits that were earned in the fourth quarter of 2008 as markets in all these asset classes fell further. Fig. 3 also shows that TSMOM suffers sharp losses when the crisis ends in March, April, and May of 2009. The ending of a crisis constitutes a sharp trend reversal that generates losses on a trend following strategy such as TSMOM.

More generally, Fig. 4 plots the TSMOM returns against the S&P 500 returns. The returns to TSMOM are largest during the biggest up and down market movements. To test the statistical significance of this finding, the first row of Panel C of Table 3 reports coefficients from a regression of TSMOM returns on the market index return and squared market index return. While the beta on the market itself is insignificant, the coefficient on the market return squared is significantly positive, indicating that TSMOM delivers its highest profits during the most extreme market episodes. TSMOM, therefore, has payoffs similar to an option straddle on the market. Fung and Hsieh (2001) discuss why trend following has straddle-like payoffs and apply this insight to describe the performance of hedge funds. Our TSMOM strategy generates this payoff structure because it tends to go long when the

[9] We thank the referee for asking for this out-of-sample study of old data.

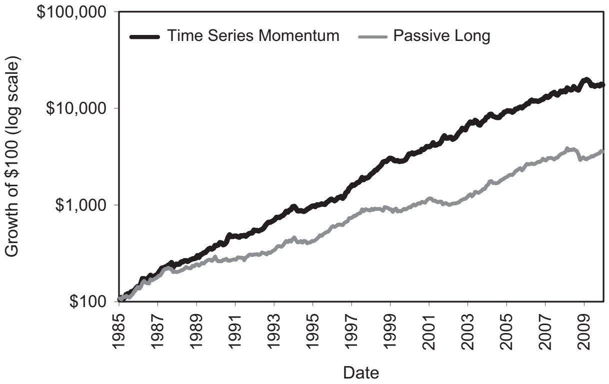

Fig. 3. Cumulative excess return of time series momentum and diversified passive long strategy, January 1985 to December 2009. Plotted are the cumulative excess returns of the diversified TSMOM portfolio and a diversified portfolio of the possible long position in every futures contract we study. The TSMOM portfolio is defined in Eq. (5) and across all futures contracts summed. Sample period is January 1985 to December 2009.

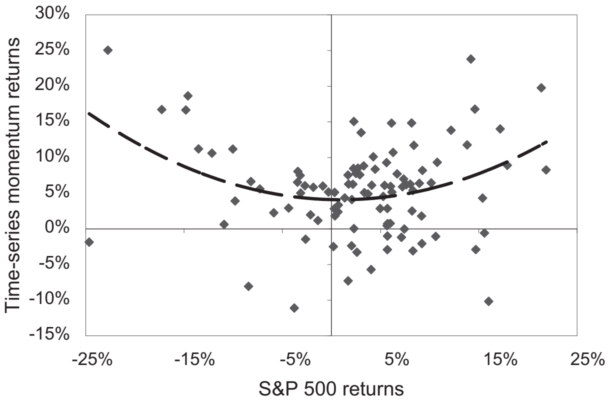

Fig. 4. The time series momentum smile. The non-overlapping quarterly returns on the diversified (equally weighted across all contracts) 12-month time series momentum or trend strategy are plotted against the contemporaneous returns on the S&P 500.

market has a major upswing and short when the market crashes.

These results suggest that the positive average TSMOM returns are not likely to be compensation for crash risk. Historically, TSMOM does well during "crashes" because crises often happen when the economy goes from normal to bad (making TSMOM go short risky assets), and then from bad to worse (leading to TSMOM profits), with the recent financial crisis of 2008 being a prime example.

4.4. Liquidity and sentiment

We test whether TSMOM returns might be driven or exaggerated by illiquidity. We first test whether TSMOM performs better for more illiquid assets in the cross-section, and then we test whether the performance of the diversified TSMOM factor depends on liquidity indicators in the time series. For the former, we measure the illiquidity of each futures contract using the daily dollar trading volume obtained from Reuters and broker feeds. We do not have historical time series of daily volume on these contracts, but use a snapshot of their daily volume in June 2010 to examine cross-sectional differences in liquidity across the assets. 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. As shown in the bottom of Figure 2, we find little relation between the magnitude of the Sharpe ratio of TSMOM for a particular contract and its illiquidity, as proxied by daily dollar trading volume. The correlation between illiquidity and Sharpe ratio of a time series momentum strategy by contract is -0.16 averaged across all contracts, suggesting that, if anything, more *liquid* contracts exhibit greater time series momentum profits.

We next consider how TSMOM returns co-vary in aggregate with the time series of liquidity. The second row of Panel C of Table 3 reports results using the Treasury Eurodollar (TED) spread, a proxy for funding liquidity as suggested by Brunnermeier and Pedersen (2009), Asness, Moskowitz, and Pedersen (2010), and Garleanu and Pedersen (2011), 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 TSMOM 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, which also seem to correspond with illiquid episodes. There is no significant relationship between TSMOM profitability and market volatility either.

At the bottom of Panel C of Table 3, we also examine the relationship between TSMOM returns and the 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 no significant relationship between TSMOM profitability and sentiment measures, even at the extremes.

4.5. 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 time 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 correlation structure reflects the comovement of the returns to simply being passive long (or short) in 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 and, except for currencies, passive long strategies exhibit higher correlations than time series momentum strategies within an asset class.

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 TSMOM portfolios across asset classes. All of the correlations are positive, ranging from 0.05 to 0.21. For comparison, the table also shows the correlations across asset classes of diversified passive long positions. For every asset class comparison, the correlation of time series momentum strategies across asset classes is larger than the corresponding correlation of passive long strategies, 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 last result suggests that there is a common component affecting time series momentum strategies across asset classes simultaneously that is not present in the underlying assets themselves, similar to the findings of Asness, Moskowitz, and Pedersen (2010) who find common structure among cross-sectional momentum strategies across different asset classes.

Table 4
Correlations of time series momentum strategy returns within and across asset classes.

Panel A reports within 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. Panel B reports the correlation of time series momentum strategies and passive long positions *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 strategies across asset classes are calculated. Correlations are calculated from monthly returns over the period January 1985–December 2009.

Panel A: Average pair-wise correlation within asset class

	Commodities	Equities	Fixed income	Currencies
TSMOM 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 TSMOM strategies			
Commodities	1			
Equities	0.20	1		
Fixed income	0.07	0.21	1	
Currencies	0.13	0.20	0.05	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

5. 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 commonly used in the literature.

5.1. Time series momentum regressed on cross-sectional momentum

Panel A of Table 5 provides further evidence on the relationship between time series momentum (TSMOM) and cross-sectional momentum (XSMOM) 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.[10]

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

The first row of Panel A of Table 5 reports results from the TSMOM strategy diversified across all assets regressed on the XSMOM strategy that is diversified across those same assets. As before, time series momentum and cross-sectional momentum are significantly related, with the beta of TSMOM on XSMOM equal to 0.66 with a t-statistic of 15.17 and R-square of 44%. However, as the intercept indicates, TSMOM is not fully captured by XSMOM, exhibiting a positive and significant alpha of 76 basis points per month with a t-statistic of 5.90. So, TSMOM and XSMOM are related, but are not the same.

The second row of Panel A of Table 5 repeats the regression using XSMOM strategies for each asset class, including individual stocks. TSMOM is related to XSMOM across all of the different asset classes, including individual equity momentum, which is not even included in the TSMOM strategy, and this is *after* controlling for exposure to XSMOM from the other four asset classes. TSMOM still exhibits a significant alpha, however, and is therefore not fully captured by cross-sectional momentum strategies in these asset classes.

Repeating these regressions using the TSMOM returns for each asset class separately, we find a consistent pattern. TSMOM is related to XSMOM within each asset class, with R-squares ranging from 56% in currencies (FX) to 14% in fixed income, but TSMOM is not captured by XSMOM. The alphas of TSMOM remain significantly positive for every asset class. We also see some interesting cross-asset relationships among TSMOM and XSMOM. For instance, not only is TSMOM for commodities correlated with XSMOM for commodities, but also with XSMOM for currencies. Likewise, TSMOM among equity index futures is not only correlated with XSMOM among those equity indexes but also with XSMOM among individual stocks. And, TSMOM for fixed income is correlated with XSMOM for fixed income and XSMOM 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).

5.2. A simple, formal decomposition

We can more formally write down the relationship between time series (TSMOM) and cross-sectional (XSMOM) 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 $w_t^{XS,i} = (1/N)(r_{t-12,t}^i - r_{t-12,t}^{EW})$, that is, the past 12-month excess return over the equal-weighted average return, $r_{t-12,t}^{EW} = (1/N)\sum_{i=1}^N r_{t-12,t}^i$. 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[11] $\mu^i = E(r_{t,t+1}^i) = E(r_{t-12,t}^i)/12$ and letting $\mu = [\mu^1,\ldots,\mu^N]'$, $R_{t,s} = [r_{t,s}^1,\ldots,r_{t,s}^N]'$, and $\Omega = E[(R_{t-12,t} - 12\mu)(R_{t,t+1} - \mu)']$, the expected return to cross-sectional momentum (XSMOM) can be decomposed as

$$\begin{aligned} E[r_{t,t+1}^{XS}] &= \frac{tr(\Omega)}{N} - \frac{1'\Omega 1}{N^2} + 12\sigma_\mu^2 \\ &= \frac{N-1}{N^2} tr(\Omega) - \frac{1}{N^2}\left[1'\Omega 1 - tr(\Omega)\right] + 12\sigma_\mu^2, \end{aligned} \tag{6}$$

where tr is the trace of a matrix, 1 is an $(N \times 1)$ vector of ones, and σ_μ^2 is the cross-sectional variance of the mean monthly returns μ^i.

Eq. (6) 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 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 $w_t^{TS,i} = (1/N)r_{t-12,t}^i$. Then the expected return is

$$E(r_{t,t+1}^{TS}) = E\left(\sum_{i=1}^N w_t^{TS,i} r_{t,t+1}^i\right) = \frac{tr(\Omega)}{N} + 12\frac{\mu'\mu}{N}. \tag{7}$$

As these equations highlight, time series momentum profits are primarily driven by time series predictability (i.e., positive auto-covariance in returns) if the average squared mean returns of the assets is small. Comparing Eqs. (6) and (7), 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 equations above. We report the three components of the cross-sectional momentum strategy: "Auto" refers to the auto-covariance or time series momentum component, "Cross" refers to the cross-serial covariance or lead-lag component, and "Mean"

[11] 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.

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 (TSMOM) on 12-month cross-sectional momentum strategies (XSMOM) 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 4.2, 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 C reports results from regressions of several XSMOM strategies in different asset classes, the Fama-French momentum, value, and size factors, and two hedge fund indexes obtained from Dow Jones/Credit Suisse on our benchmark TSMOM factor.

Panel A: Regression of TSMOM on XSMOM

		Independent variables							
		XSMOM ALL	XSMOM COM	XSMOM EQ	XSMOM FI	XSMOM FX	XSMOM US stocks	Intercept	R^2
Dependent variable	TSMOM ALL	0.66						0.76%	44%
		(15.17)						(5.90)	
	TSMOM ALL		0.31	0.20	0.17	0.37	0.12	0.73%	46%
			(7.09)	(4.25)	(3.84)	(8.11)	(2.66)	(5.74)	
	TSMOM COM		0.65					0.57%	42%
			(14.61)					(4.43)	
	TSMOM COM		0.62	0.05	0.02	0.14	0.05	0.51%	45%
			(13.84)	(1.01)	(0.50)	(3.08)	(1.06)	(3.96)	
	TSMOM EQ			0.39				0.47%	15%
				(7.32)				(3.00)	
	TSMOM EQ		0.07	0.28	0.04	0.06	0.24	0.43%	22%
			(1.29)	(5.07)	(0.67)	(1.11)	(4.26)	(2.79)	
	TSMOM FI				0.37			0.59%	14%
					(6.83)			(3.77)	
	TSMOM FI		−0.03	0.18	0.34	0.01	0.03	0.50%	17%
			(−0.62)	(3.05)	(6.19)	(0.20)	(0.48)	(3.15)	
	TSMOM FX					0.75		0.42%	56%
						(19.52)		(3.75)	
	TSMOM FX		0.04	0.00	−0.01	0.75	−0.01	0.40%	56%
			(1.07)	(−0.04)	(−0.17)	(18.89)	(−0.24)	(3.49)	

Panel B: Decomposition of TSMOM and XSMOM

	XSMOM decomposition				TSMOM 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%

Panel C: What factors does TSMOM explain?

		Independent variable		
		TSMOM ALL	Intercept	R^2
Dependent variable	XSMOM ALL	0.66	−0.16%	44%
		(15.17)	(−1.17)	
	XSMOM COM	0.65	−0.09%	42%
		(14.61)	(−0.66)	
	XSMOM EQ	0.39	0.29%	15%
		(7.32)	(1.86)	
	XSMOM FI	0.37	−0.14%	14%
		(6.83)	(−0.87)	
	XSMOM FX	0.75	−0.19%	56%
		(19.52)	(−1.71)	
	UMD	0.49	−0.28%	13%
		(6.56)	(−0.93)	
	HML	−0.07	0.43%	1%
		(−1.46)	(2.08)	
	SMB	−0.01	0.10%	0%
		(−0.26)	(0.49)	
	DJCS MF	0.55	−0.30%	33%
		(9.60)	(−1.37)	
	DJCS MACRO	0.32	0.52%	14%
		(5.64)	(2.38)	

refers to the contribution from unconditional mean returns, as well as their sum ("Total"). We also report the two components to TSMOM: 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* to XSMOM and the cross-sectional variation in means has a small positive contribution to 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 the auto-covariance of returns. Squared mean excess returns are a much smaller component of TSMOM profits, except for fixed income. Since the cross-sectional correlation of lead-lag effects among assets contributes negatively to XSMOM, it is not surprising that TSMOM, which does not depend on the cross–serial correlations across assets, produces higher profits than XSMOM.

We also regress the returns of time series momentum as defined in Eq. (7) (which is linear as opposed to using the sign of the past return as before) on the returns to cross-sectional momentum as defined in Eq. (6). We find that time series momentum has a significant alpha to cross-sectional momentum, consistent with our earlier results in Panel A of Table 5 that use a slightly different specification. We investigate next whether the reverse is true. Does TSMOM explain XSMOM?

5.3. Does TSMOM explain cross-sectional momentum and other factors?

Panel C of Table 5 uses TSMOM as a right-hand-side variable, testing its ability to explain other factors. We first examine XSMOM to see if TSMOM can capture the returns to cross-sectional momentum across all asset classes as well as within each asset class. As the first five rows of Panel C of Table 5 show, TSMOM is able to fully explain cross-sectional momentum across all assets as well as within each asset class for commodities, equity indexes, bonds, and currencies. The intercepts or alphas of XSMOM are statistically no different from zero, suggesting TSMOM captures the return premiums of XSMOM in these markets. The only positive alpha is for XSMOM in equity indexes, which has a marginal 1.86 t-statistic. We also regress the Fama-French cross-sectional momentum factor for individual US equities, UMD, on our TSMOM portfolio. The UMD factor is created from individual US equities and hence has no overlap with any of the assets used to comprise our TSMOM factor. Nevertheless, TSMOM is able to capture the return premium to UMD, which has a positive 0.49 loading on TSMOM and an insignificant -0.28 alpha (t-stat$=-0.93$). We also examine the other Fama-French factors HML, the value factor, and SMB, the size factor. HML loads negatively on TSMOM, so TSMOM naturally cannot explain the value effect, and SMB has a loading close to zero.

Finally, we also examine the returns to two popular hedge fund indexes that trade globally across many assets: the "Managed Futures" hedge fund index and "Global Macro" hedge fund index obtained from Dow Jones/Credit Suisse from 1994 to 2009. As the last two rows of Panel C of Table 5 show, both hedge fund indexes load significantly on our TSMOM factor and in the case of the Managed Futures index, the TSMOM factor captures its average return entirely. Hence, TSMOM is a simple implementable factor that captures the performance metric of Fung and Hsieh (2001), which they show explains hedge fund returns as well.[12]

The strong performance of TSMOM and its ability to explain some of the prominent factors in asset pricing, namely, cross-sectional momentum as well as some hedge fund strategy returns, suggests that TSMOM is a significant feature of asset price behavior. Future research may well consider what other asset pricing phenomena might be related to time series momentum.

6. Who trades on trends: Speculators or hedgers?

To consider who trades on time series momentum, Fig. 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, Fig. 5 plots the average Net speculator position in, respectively, the subsample where the past 12-month return on the contract is positive ("Positive TSMOM") and negative ("Negative TSMOM") 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 time series momentum is associated with positive abnormal returns, these results indicate that speculators profit, on average, from these position changes at the expense of hedgers.

6.1. The evolution of TSMOM

We next consider the dynamics of these trading positions over time. Our previous results suggest that 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 TSMOM and trading patterns may help distinguish theories for momentum. For

[12] Lequeux and Acar (1998) also show that a simple timing trade tracks the performance of currency hedge funds.

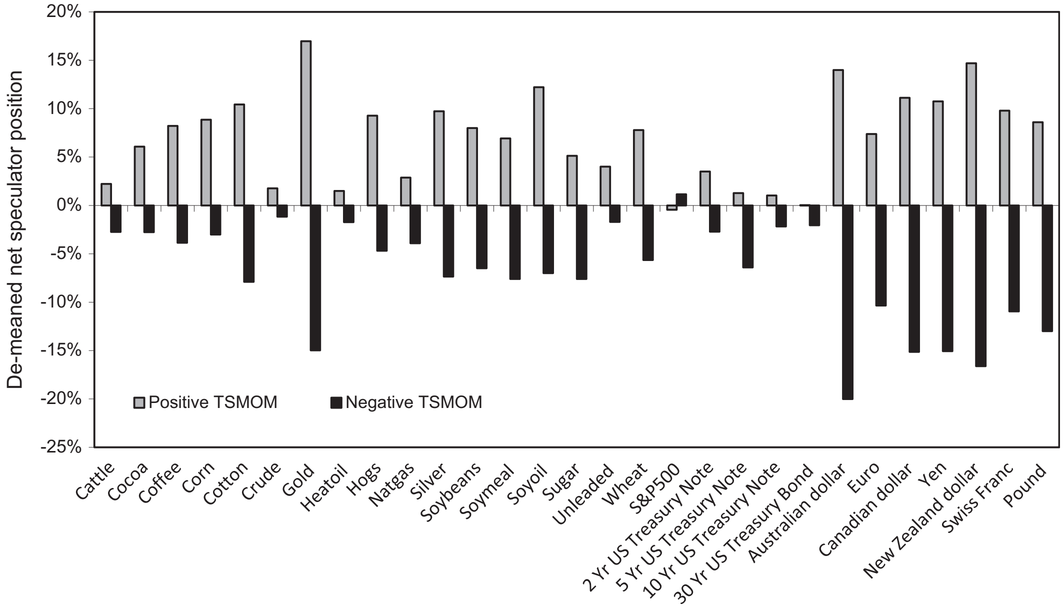

Fig. 5. Net speculator positions. For each futures contract, the figure plots the average de-meaned Net speculator position in, respectively, the subsample where the past 12-month returns on the contract are positive ("Positive TSMOM") and negative ("Negative TSMOM"). The figure illustrates that speculators are on average positioned to benefit from trends, whereas hedgers, by definition, have the opposite positions.

example, if initial under-reaction to news is the cause of TSMOM, 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 TSMOM, we perform an event study as follows. For each month and instrument, we first identify whether the previous 12-month 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 TSMOM") and negative past-year returns ("Negative TSMOM"), respectively, where we normalize the cumulative returns to be one at the event date.

Panel A of Fig. 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 sentiment theories such as Daniel, Hirshleifer, and Subrahmanyam (1998) and Barberis, Shleifer, and Vishny (1998). 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 as well. Similarly, the negative pre-formation trend is continued for a year until it partially reverses as well.

Panel B of Fig. 6 shows the evolution of Net speculator positions that coincide with the positive and negative time 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 portfolio formation for both positive and negative trends. We see that for positive TSMOM, speculators increase their positions steadily from months -12 to 0, building up to the formation date. Likewise, speculators decrease their positions steadily from the negative TSMOM event date. These patterns are not by construction since we split the sample based on returns and not based on Net speculator positions. After the event date, speculators' positions begin to mean-revert towards their (positive) average levels, and plateau at about a year (and maybe slightly longer for negative TSMOM), which is when the trend in returns starts to reverse.

The patterns in Fig. 6 indicate that while speculator positions are consistent with trading on TSMOM, they do not appear to keep piling into the trade with a lag. In fact, speculators appear to reduce their trend chasing up to the point where positive returns from following TSMOM 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 over-reaction 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

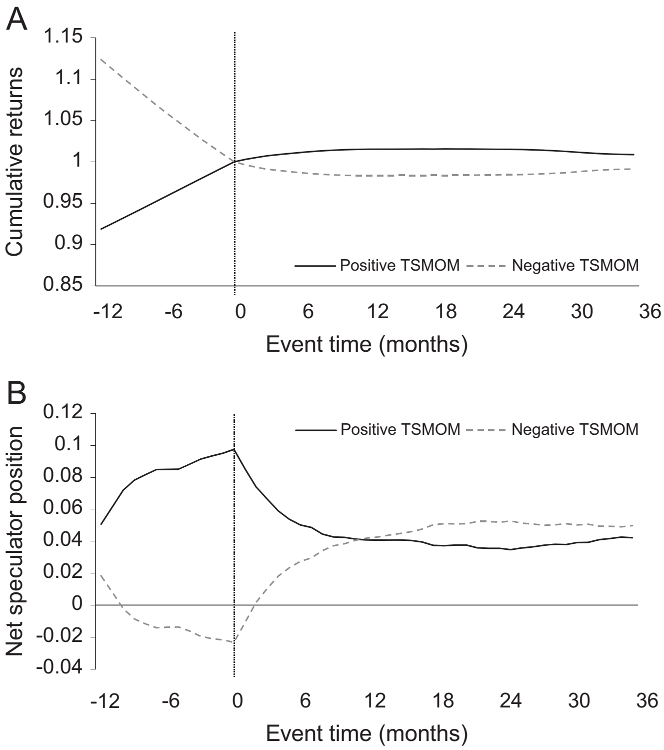

Fig. 6. Event study of time series momentum. For each month and instrument, we identify whether the previous 12-month returns are positive or negative and compute the average return from 12 months prior to the "event date" (portfolio formation date) to 36 months after following positive past-year returns ("Positive TSMOM") and negative past-year returns ("Negative TSMOM"). 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. (A) *Panel A*: Cumulative returns in event time; (B) *Panel B*: Net speculator positions in event time.

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.

6.2. 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 need to include more than 12 months of lags to capture delayed reversal, but our results are robust to choosing other lag lengths between 12 and 24.

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 return response to an initial return shock is qualitatively the same regardless of the ordering of the Cholesky decomposition because of a limited feedback with positions.) The response to this impulse is plotted in Fig. 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 at about a year. 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 TSMOM for about a year and then revert to their average positions at the same time the TSMOM effect ends; all at the expense of hedgers.

The patterns indicate that speculators profit from time series momentum, while hedgers pay for it. One explanation might be that speculators earn a premium through time series momentum for 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. Specifically, we investigate whether changes in the underlying spot price or the 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.

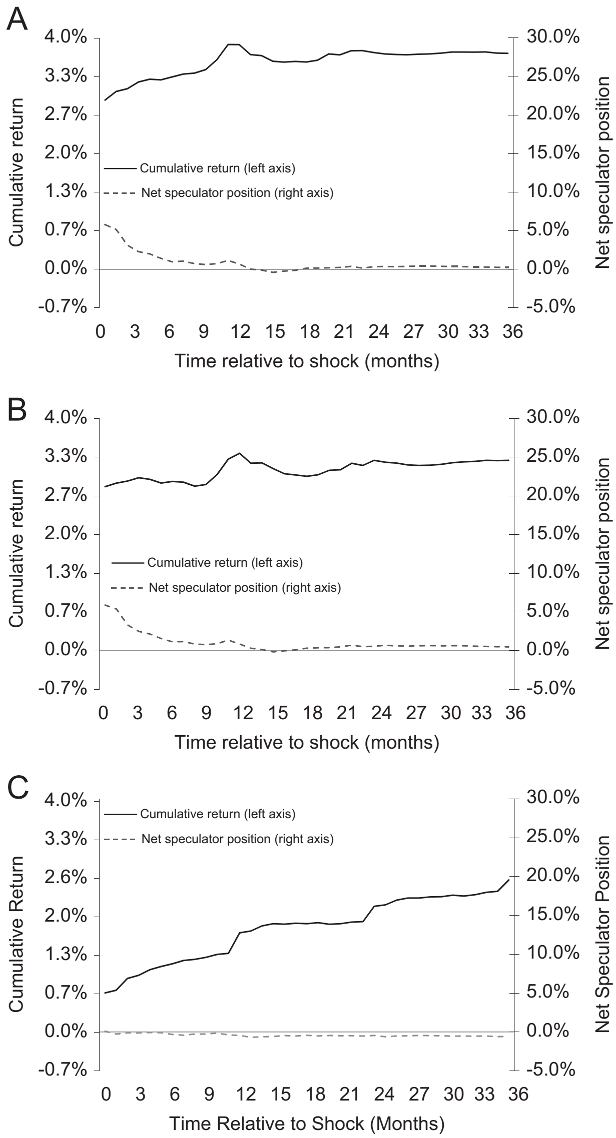

Fig. 7. Impulse response from a shock to returns. Plotted are the cumulative returns and speculators' net positions in response to a one standard deviation shock to total returns on the futures contract (Panel A), returns on the spot asset (Panel B) and returns to rolling the contract (Panel C). The 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. (A) *Panel A*: Futures returns; (B) *Panel B*: Spot returns; (C) *Panel C*: Roll returns.

6.3. 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 define the underlying spot price changes in excess of the risk-free rate as

$$Price\ change_{t-12,t} = \frac{Price_t - Price_{t-12}}{Price_{t-12}} - r^f_{t-12,t}\,,$$

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

$$Futures\ return_{t-12,t} = Price\ change_{t-12,t} + Roll\ return_{t-12,t}.$$

In financial futures with little storage costs or convenience yield, the roll return is close to zero, but, in commodity markets, the roll return can be substantial. The futures return is calculated from the nearest-to-expiration or next-to-nearest expiration contract, whose maturity date may not be in the same month as the spot return calculation, which is based only on the nearest-to-expiration contract.

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 TSMOM"), previous 12 months' change in spot price ("Spot price MOM"), past 12-month roll return ("Roll MOM"), and the 12-month change and average level in speculators' aggregate net (i.e., long minus short) positions as a percent of open interest ("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 TSMOM	Spot price MOM	Roll MOM	Chg net speculator position	Net speculator position	Spot MOM × Chg net spec pos	Roll MOM × Chg net spec pos	Intercept	R^2
Coefficient	0.019							0.09%	0.6%
t-Stat	(3.57)							(1.31)	
Coefficient		0.014						0.12%	0.3%
t-Stat		(2.29)						(1.71)	
Coefficient			0.024					0.08%	0.3%
t-Stat			(3.22)					(1.08)	
Coefficient				0.007				0.12%	0.2%
t-Stat				(2.67)				(1.63)	
Coefficient					0.007			0.08%	0.2%
t-Stat					(2.33)			(1.12)	
Coefficient	0.017			0.004				0.09%	0.7%
t-Stat	(3.13)			(1.65)				(1.33)	
Coefficient	0.018				0.002			0.08%	0.6%
t-Stat	(3.31)				(0.76)			(1.14)	
Coefficient		0.017	0.030					0.08%	0.6%
t-Stat		(2.74)	(3.90)					(1.03)	
Coefficient		0.014	0.030	0.005				0.07%	0.8%
t-Stat		(2.12)	(3.94)	(1.89)				(0.99)	
Coefficient		0.014	0.030	0.005		0.023	0.015	0.06%	0.8%
t-Stat		(2.17)	(3.94)	(1.78)		(1.38)	(0.49)	(0.77)	

Our conjecture is that hedgers' price pressure affects mostly the roll returns, whereas information diffusion affects mostly spot price changes. To see why, recall first Keynes' (1923) 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 Fig. 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 Fig. 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 periods of time 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 and level of Net speculator positions. The first five rows of Table 6 report the univariate regression results for each of these variables, which are all significant positive 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 for hedging pressure. Spot price changes and roll returns have almost the same predictive regression coefficient in the multivariate regression, hence, 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 speculator positions. While all the coefficients are positive, indicating that when changes in Net speculator positions move in the same direction as returns, there is stronger positive predictability of future returns, the results are not statistically significant.

The results in Table 6 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 speculator and hedging positions. Speculators seem to ride the trend for about a year, eventually reducing their positions and taking the opposite side before it 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.

7. Conclusion

We find 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 25 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 it's lagged 1-year return. This evidence is consistent with initial under-reaction stories, but may also be consistent with delayed over-reaction theories of sentiment as the time series momentum effect partially reverses 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, all of which present a challenge to the random walk hypothesis and to standard rational pricing 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 and is highly correlated across very different asset classes. Indeed, correlation among time series momentum returns is stronger than the correlation of passive long positions across the same asset classes, implying the existence of a common component to time series momentum that is not present in the underlying assets themselves.

Finally, the link between time series momentum returns and the positions of speculators and hedgers indicates that speculators profit from time series momentum at the expense of hedgers. This evidence is consistent with speculators earning a premium via time series momentum for providing liquidity to hedgers. Decomposing futures returns into the effect of price changes, which captures information diffusion, and the roll return, which captures 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 profits. However, only shocks to price changes partially reverse, consistent with behavioral theories of delayed over-reaction to information, and not hedging pressure.

Time series momentum represents one of the most direct tests of the random walk hypothesis and a number of prominent behavioral and rational asset pricing theories. Our findings present new evidence and challenges for those theories and for future research.

Appendix A. Data sources

A.1. Equity indexes

The universe of equity index futures consists of the following nine developed equity markets: SPI 200 (Australia), CAC 40 (France), DAX (Germany), FTSE/MIB (Italy), TOPIX (Japan), AEX (Netherlands), IBEX 35 (Spain), FTSE 100 (UK), 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.

A.2. Bond indexes

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.

A.3. Currencies

The universe of currency forwards covers the following ten exchange rates: Australia, Canada, Germany spliced with the Euro, Japan, New Zealand, Norway, Sweden, Switzerland, UK, and US 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, respectively. Prior to that, we use spot exchange rates from Datastream and Interbank Offered Rate (IBOR) short rates from Bloomberg to calculate returns.

A.4. Commodities

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

A.5. Position of traders data

We obtain speculator net length and open interest data from the CFTC Commitments of Traders Report Web site for the following futures: Corn, Soybeans, Soy Meal, Soy Oil, Wheat traded on Chicago Board of Trade (CBOT), Live Cattle, Lean Hogs, 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.

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