Time Series Momentum and Macroeconomic Risk

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Time Series Momentum and Macroeconomic Risk

The time series momentum strategy has been shown to deliver consistent profitability over a long time horizon. Funds pursuing these strategies are now a component of many institutional portfolios, due to the expectation of positive returns in equity bear markets. However, the return drivers of the strategy and its performance in other economic conditions are less well understood. The authors find evidence that the returns to the strategy are connected to the business cycle. Returns are positive in both recessions and expansions, but profitability is especially high in expansions. About 40% of returns are due to time varying factor-related risk exposure, consistent with rational asset pricing theories having a role in explaining the profitability of the strategy.

1. Introduction

Subsequent to strong performance in the 2008 financial crisis Commodity Trading Advisors (CTAs) pursuing time series momentum strategies have experienced large inflows and are now a feature of many institutional investor portfolios.[1] For many investors the intuition behind including CTAs in their portfolio is primarily the expectation of high performance during equity bear markets.[2]

Though choosing a strategy due to an expectation of positive performance during these periods is reasonable, it disregards the drivers of profitability of the strategy and may convey the idea that high returns are exclusive to equity bear markets. Unlike traditional asset classes or other hedge fund strategies, there is scant academic evidence to date on the interaction between the returns of time series momentum and the business cycle. While the academic literature does show that the strategy has historically generated consistently positive returns, and that at least a portion of time series momentum returns are due to behavioural factors, it is a common sentiment amongst investors that performance is equity market period specific.

In our paper, to help investors understand the drivers of profitability, we explicitly test the connection between time series momentum strategies and the business cycle. We arrive at four key findings. First, time series momentum portfolio returns exhibit statistically significant differences across the business cycle. While positive in both, typically the performance of the portfolio is higher in economic expansions than recessions. Second, we show that though a linear macroeconomic factor model has little explanatory power, a model which allows the coefficients to vary through time, does result in several of the

[1] According to data from Barclayhedge as of the 3rd Quarter of 2014 CTA assets under management (AUM) was $312.6 billion.
[2] See, for example, "Global worries forecast to boost flow of assets", Financial Times, June 9th 2012.

macroeconomic factors having a statistically significant relationship with time series momentum. Third, we show that when time series momentum portfolios are formed on either the factor-related or asset-specific portions of financial futures returns they generate statistically significant excess returns in both cases, with about 40 percent of returns coming from the factor-related portion. Finally, using a new estimation approach, we find that time series momentum generates higher returns in periods when economic uncertainty is lower.

From a practitioner's perspective, these results show that there is a role for rational asset pricing in explaining at least a portion of the returns to time series momentum; the strategy is related to macroeconomic risk factors which have previously been shown to be important in explaining the returns of both traditional and hedge fund portfolios; and perhaps most importantly, our evidence points to how practitioners can expect performance to vary across different future macroeconomic environments. In the next section we review the related literature and discuss how our results link to and extend this literature.

2. Literature review

The literature on time series momentum is typically focused on the performance of different variations of these strategies for particular markets in specific periods (see for example Erb and Harvey (2006), Miffre and Rallis (2007) and Fuertes *et al.* (2010) for commodities, and Okunev and White (2003) and Menkhoff *et al.* (2012) for currencies). The evidence of these studies is generally positive on the performance of time series momentum with positive Sharpe ratios and little correlation with traditional asset classes. Our paper compliments Moskowitz *et al.* (2012) who introduce multi asset class time series momentum to the literature. In a comprehensive study Moskowitz *et al.* (2012) investigate how time series momentum relates to market movements, sentiment, and the positions of speculators; finding evidence supporting a behavioural explanation for time series momentum profitability. Our study builds upon Moskowitz *et al.* (2012) in that we focus on macroeconomic factors which have been shown to be important for hedge funds and traditional portfolios, employ methodologies which directly incorporate time variation in factor exposures, and provide evidence that rational asset pricing may also be important in explaining returns.

Recent evidence linking time series momentum and the broader macroeconomy (Hutchinson and O'Brien (2014)) shows that following each of the six largest financial crises in the last hundred years, there was an extended period where time series momentum performance was below average. Though Hutchinson and O'Brien (2014) suggest several explanations why the performance of the strategy might differ in different economic conditions, unlike our study, they provide no empirical evidence connecting the strategy to the business cycle. The present paper also addresses a gap in Hutchinson and O'Brien (2014) by identifying the link between the business cycle and their finding that time series momentum tends to perform below average following periods of financial crisis. Using a new methodology, we document that uncertainty around changes in macroeconomic factors is the transmission mechanism linking the below average returns following large global financial crises and the business cycle.

By finding a link between the macroeconomy and time series momentum in a time varying framework we build upon several related papers on time series and cross sectional momentum.[3] The cross sectional momentum literature finds a strong relationship between macroeconomic factors and returns (Chordia and Shivakumar (2002)). While, to date, no one has considered this specification for time series momentum, related literature has

[3] As noted by Moskowitz *et al.* (2012) cross sectional momentum and time series momentum are related but different strategies. The key difference being that cross sectional momentum trading decisions are based upon the historical return of a security relative to other securities, whereas time series momentum is based upon the historical return of a security, considered independent of other securities. See Goyal and Jegadeesh (2015) for a decomposition of both strategies.

demonstrated the lack of explanatory power for a range of traditional factors in a linear framework (Menkhoff *et al.* (2012) and Moskowitz *et al.* (2012)).[4] We find that the relationship between returns and macroeconomic factors is only revealed in a model which explicitly allows for time varying exposure to risk factors. However, our conditional model results show that a significant portion of time series momentum returns are not explained by the macroeconomic factors.

Within the cross sectional momentum literature Conrad and Kaul (1998) argue that profitability is due to differences in cross sectional expected returns. Illustrating this, Chordia and Shivakumar (2002) demonstrate that when the returns of the underlying equities into are divided into macroeconomic factor-related and asset-specific components, the majority of cross sectional momentum profitability comes from the portion of equity returns explained by macroeconomic factors. Contrary to this, in the first study to consider the returns of time series momentum from this perspective, we find that the returns to our portfolios are attributable to both the asset-specific and factor-related components of financial futures.

More recently, the hedge fund literature has linked the performance of a range of hedge fund strategies to economic uncertainty. Bali *et al.* (2014) find that the sensitivity of hedge funds to uncertainty about the economy is important in explaining the cross sectional deviation in their performance. In the first study to apply this methodological approach to time series momentum, our evidence suggests that time series momentum returns tend to be higher when economic uncertainty is lower than average.

3. Data and methods

[4] We acknowledge that the broad range of drivers of returns investigated by Moskowitz *et al.* (2012) do relate to time variation in strategy performance.

In this section we describe the selection of the sample period and the data used in the analysis. The dataset consists of individual exchange traded futures contracts, synthetic forward contracts and a range of macroeconomic variables.

3.1 Futures data

In this paper we investigate the relationship between macroeconomic variables and the returns of the time series momentum investment strategy. As consistent monthly macroeconomic data only becomes available from the late 1940s, we specify January 1950 as the starting point for the analyses.[5] The sample period runs to the end of September, 2014. We split the sample into two sub-periods, January 1950 to December 1979 and January 1980 to September 2014, based around the peak of the great inflation. The first period is characterised by high inflation and increasing interest rates, whereas from 1980 inflation fell quickly and remained in a range of 2% to 5% for most of that period.[6] In this second sub-period interest rates fell steadily, from a high of 15.5% in 1981 to a low of 1.7% in 2012.[7] Dividing the sample into these two sub-periods allows us to assess performance in different long term interest rate cycles.

The futures data set consists of twenty one commodities, thirteen government bonds, twenty one equity indices and currency crosses derived from nine underlying rates covering the period from January 1949 to September 2014. The data consists of a combination of exchange traded futures data and forward prices derived from historical data. The momentum signals and portfolio returns are based on continuous return series. Using only exchange traded futures contracts would limit the time frame of the study to post-1980. In order to extend the study period backwards we follow the methodology used in other long term

[5] We also use data for the twelve months prior to January 1950 to generate trading signals for the initial time series momentum portfolios.
[6] Annual change in US CPI, source Federal Reserve Economic Database.
[7] US Treasury 10 Year yield, source Federal Reserve Economic Database.

studies of time series momentum (see, for example, Hurst *et al.* (2012)) and combine exchange traded prices with synthetic forwards created from the underlying instruments. Exchange traded futures' prices are available from Datastream from 1980 to the present. Prior to this period, we obtain continuous return series for commodity futures from Commodity Systems Inc. and MSCI currency data from Datastream. All older data is sourced from Global Financial Data. Table 1 shows a full list of the futures used in the study and data sources are discussed in greater detail in Appendix A.

[Insert Table 1 here]

Where a futures contract trades on an exchange, the return series of the individual futures contracts are combined to produce a continuous excess return series. Where futures contracts are not available, forward prices are created by combining the underlying spot price, yield and risk free rate. These two approaches are discussed below.

Continuous returns from futures contracts

Continuous return series are created from futures where daily price and volume data is available. We calculate the daily excess return of the most liquid contract. This is generally the front month or the next-nearest to delivery month. We select the most liquid contract as follows. At time, t, the average volume over the previous three trading days is measured for each of the live delivery dates. We select the contract with the highest volume to be recorded as the excess return for that day. To replicate the practicalities of rolling contracts, once we select a further delivery month, we do not allow the excess return of nearer delivery months to be selected again.

Continuous return forward prices

Where exchange traded futures are not available, excess return series are created from the underlying spot price, risk free rate and yield. The excess return from buying a forward at the start of a month and holding it to month end, er_1, is given by:

$$er_1 = (1 + r_1)\left(\frac{1+q}{1+r_f}\right)^{(1/12)} - 1 \tag{1}$$

where r_1 is the spot price return for the month, r_f is the one month risk free rate, and q is the annualized yield. In order to confirm the validity of using synthetic forwards, a number of tests were carried out where exchange traded futures returns were replaced by synthetic forward returns. The series were typically almost perfectly correlated and in all cases results were close to identical.

3.2 Economic data

Recent evidence has documented a strong link between macroeconomic risk and hedge fund strategies (Bali *et al.* (2014)). Due to the power of these factors for hedge funds we specify the economic factors presented in Bali *et al.* (2014) for all analyses.[8] Consistent with Bali *et al.* (2014) we use the Federal Reserve Economic Database, the Bureau of Labour Statistics and the online data libraries of Robert Shiller and Kenneth French for economic data. A more detailed description of the sources can be found in Appendix A. Information is available for all eight factors from January 1950 to September 2014. We also examine the performance of time series momentum portfolios in periods of economic expansion and recession, based on definitions from the National Bureau of Economic Research (NBER) and GDP data from the Federal Reserve.

3.3 Time series momentum portfolio

[8] For robustness we also conducted all analyses using Chordia and Shivakumar (2002) and Chen *et al.* (1986) factors. The results (unreported) for all analyses, with the exception of economic uncertainty, were stronger with these alternative specifications.

The analyses of time series momentum in this paper are based on time series representing the performance of the strategy across four distinct asset class sub-portfolios and a diversified portfolio combining the four sub-portfolios.

The portfolios and their associated return series are created from the excess returns of the instruments in the data universe. Where possible, excess returns are taken directly from futures contracts trading on public exchanges, with the return of the most active contract, defined as a function of trade volume, used as the excess return. Where futures exchange data is not available for earlier periods, synthetic forward prices are created by combining the underlying spot price, yield and risk free rate.

In creating the time series of time series momentum portfolios we use a twelve month formation (look-back) period and a one month holding period.[9] These are the most common definitions used in the literature (see, for example, Hurst *et al.* (2012), Moskowitz *et al.* (2012) and Baltas and Kosowski (2013)). The first step is to assign each instrument a momentum signal, defined as

$$M_{t,k}^{i} = sign\left(\sum_{1}^{k} \log\left(1 + r_{t-k}^{i}\right)\right) \tag{2}$$

Where, $M_{t,k}^{i}$ is the momentum of instrument i at time t formed with a look back period of k months and r_{t-k}^{i} is the excess return of instrument i at time t - k.

The instruments are divided into four asset classes, Equity Indices, Government Bonds, Foreign Exchange and Commodities and a time series momentum portfolio is created for each class. Each instrument is given a weight proportional to its momentum signal and inversely proportional to its volatility, so the size of the position is

[9] Repeating the analyses using a range of different parameters, including the momentum signal defined in Hutchinson and O'Brien (2014), produces very similar results.

$$w_t^i = \frac{1}{N_c} M_t^i . \frac{V_o}{\sigma_t^i} \quad (3)$$

Where w_t^i is the weight of instrument *i* held in the portfolio at time t and σ_t^i is the corresponding volatility. N_c is the number of instruments in the asset class. This adjusts the weights so that each sub-portfolio is allocated the same level of risk irrespective of the number of assets in the class.[10] The position is scaled by V_o, the choice of this is arbitrary, but is set at 40% so the resulting return series have volatility levels in a range from 10% to 15%, equivalent to those reported in the literature, allowing easier comparison (Moskowitz *et al.* (2012)). The portfolio is rebalanced monthly[11] so the return series for each sub-portfolio is

$$r_t^c = \sum_{i=1}^{N_c} \left(r_t^i . w_t^i \right) \quad (4)$$

Where r_t^c is the excess return of sub-portfolio c in time period *t*. The time series for the diversified portfolio is the sum of the return series of the four sub-portfolios.[12]

Ex-ante volatility

We replicate the methodology of Moskowitz *et al.* (2012) to create the ex-ante volatility estimates. This method uses an exponentially weighted squared daily returns model to estimate volatility, a model similar to a univariate GARCH model. The annualised volatility for each instrument is calculated as:

$$\sigma_t = \sqrt{261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \overline{r_t})^2} \quad (5)$$

The parameter δ is chosen so that the center of mass of the weights is 60 days, so data from the last sixty days carries equal weight to all data up to then. The same model is used for all instruments.

[10] Risk levels are not exactly matched as we do not include correlation between assets.
[11] The portfolio construction does not allow for intra-month changes in volatility.
[12] In periods where there are fewer than four portfolios, returns are scaled so the diversified portfolio has constant target volatility throughout the entire sample period.

Transaction costs are included in the performance measures in this paper, using the cost model described by Hurst *et al.* (2012), where costs are a function of asset class and time. All returns presented are in excess of the risk free rate. In general results are presented for three time periods: the entire sample period, January 1950 to September 2014; and two sub-periods, January 1950 to December 1979 and January 1980 to September 2014.[13]

The cumulative excess return of the diversified portfolio is shown in Figure 1 and the summary performance statistics for the diversified portfolio and the four asset class sub-portfolios are presented in Table 2.

[Insert Figure 1 here]

[Insert Table 2 here]

The most striking feature is the consistent excess returns generated by the time series momentum strategy in the long run. The diversified portfolio and all sub-portfolios are positive over the full period and both sub-periods. Over the full sample the diversified portfolio generates a mean annualised excess return of 15.75% with a volatility of 12.55% which translates into a Sharpe ratio of 1.25. The pattern of strong positive returns is consistent with studies of time series momentum strategies by Moskowitz *et al.* (2012) for the period 1985 to 2009 and Hurst *et al.* (2012) who examine an extended period from 1903 to 2012. It is also notable that there is little difference in performance for the diversified portfolio or the Bond sub-portfolio between the two sub-periods, despite the dramatically different interest rate regimes.

4.0 Time series momentum across the economic cycle

[13] FX results do not begin until August 1972, so results reported for this asset class in the earlier sub-period are based on a relatively short sample period.

To examine the performance of time series momentum across the economic cycle, we initially measure and compare the performance of time series momentum in different economic states. The states are defined as a function of an economic or interest rate spread variable. Each month's return is assigned to one of the two possible states. The average performance of the strategy in each state is calculated as the annualised mean of the pooled excess returns for that state.

The variation in performance of time series momentum under different economic and interest rate spread states is analysed here, first for the business cycle using two different definitions of recession, and then by using interest rate spreads (term and default) to define the state.

Economic states

The variation in performance of time series momentum under different economic conditions is tested by splitting the return of the time series momentum return series according to the contemporaneous economic state. The economy is allowed to be in one of two states, expanding or contracting. Two definitions of economic state are used. The first uses NBER recession definitions to define the state of the economy as contracting, with all other periods defined as expanding. The second uses the sign of the change in GDP to define the economic state; a positive change corresponded with an expansion and a negative change with a recession.[14] The results are displayed in Table 3.

[Insert Table 3 here]

Using either definition, the economy expands in approximately 85% of months and contracts in 15% of months, a pattern repeated in both sub-periods. Irrespective of the

[14] There is overlap between four of the ten NBER recessions analysed here and four of the five post-1950 global financial crises twenty four month periods examined in Hutchinson and O'Brien (2014) , though the NBER recessions are much shorter (average peak to trough length of 11.1 months).

definition the results of the analysis are consistent. The diversified, equity, bond and FX portfolios generate higher returns in periods of expansion than recession. This is seen over both the full sample and, in general, across the sub-periods.[15] Over the full period the average performance in expansions exceeds that in recessions by a statistically significant 8.5% (NBER) and 7.6% (GDP).

Consistent with the results of Hutchinson and O'Brien (2014) the commodity portfolio provides an exception to this pattern, performing better in recessions than expansions, returning 3.58% in recessions against 1.86% in expansions (NBER definition). This result highlights the diversification benefits of commodities in a time series momentum portfolio.

Spread states

In order to further explore the relationship between economic conditions and the performance of times series momentum we define economic conditions using two key interest rate spreads. These proxy for short term (term spread) and long term (default spread) peaks and troughs in the business cycles (Fama and French (1989)). The term spread is defined as the difference between the 10 year and three month US treasury rate and the default spread is the difference between the BAA and AAA rated US corporate bonds.

In the following analyses, a month is defined as High (Low) if the value of the variable in that month is higher (lower) than the mean for the sample period.[16] The results are displayed in Table 4.

[Insert Table 4 here]

[15] In the first sub-period bond time series momentum returns are marginally greater in expansion periods using the NBER measure (5.60% compared to 5.05%), while they are marginally smaller using the GDP measure (5.51% against 5.57%).

[16] The definition of months as high (low) in a sub period is defined relative to the mean value for that sub-period. This can lead to months being defined differently depending on the sample period mean.

The diversified portfolio performs better in periods where the term spread is low, at business cycle peaks. It generates a return of 18.76% in the low term spread state compared to 11.95% in the high state over the full period, a statistically significant difference of 6.8%. It also performs better in the low state relative to the high state in both sub-periods. In general the sub-portfolios also outperform in the low term spread state over the full period and both sub-periods.[17]

The pattern is repeated when looking at the default spread, where the time series momentum portfolios perform better in the low state, a proxy for expansions. Here the diversified portfolio generates a statistically significantly different return of 17.84% in the low spread state compared to 12.69% in the high state. Again, looking at the sub-portfolios and sub-periods, all typically perform better in the low default spread state compared to the high state.

5.0 Economic factor model analysis

The Bali *et al.* (2014) model has eight economic and financial factors which have been shown to be particularly important for hedge funds. The factors are commonly used in literature, examples of which can be found in the models of Chen *et al.* (1986), Fama and French (1989) and Chordia and Shivakumar (2002).

The term structure (TERM) and default spread (DEF) are included in all three of the models listed above. Fama and French (1988) show that the variables track the long term and short term business cycles, respectively. The dividend yield (DIV) is associated with mean reversion in the stock markets and can also be interpreted as a proxy for time variation in risk premia (Chordia and Shivakumar (2002)). The change in GDP and the level of unemployment (UNEMP) capture current economic conditions. Short term interest rates

[17] There is one exception; in the 1950 to 1979 sub-sample period the equity portfolio marginally outperforms in the high term spread state.

(RREL) capture both expectations about future economic activity (Chordia and Shivakumar (2002)) and predict future equity market returns. Market returns (MKT) reflect changes in expectations of future growth.[18]

The definitions of the eight factors are given in Table 5.

[Insert Table 5 here]

The ability of the economic model to explain time series momentum returns is tested using two different sets of assumptions. First, that the relationship between the factors and the methodologies is constant through time, a linear factor (unconditional) model and then allowing the relationship to vary through time (conditional model).

5.1 Linear factor model

The linear factor model specifies economic factors as explanatory variables in the regression model

$$r_t^{tf} = \beta_0 + \sum_{n=1}^{N} \beta_n EF_t^n + \varepsilon_t \tag{6}$$

Where EF_t^n is the value of economic factor *n* at time *t*. N is the total number of explanatory variables (economic factors) and r_t^{tf} is the return of the time series momentum portfolio in time period *t*. The factor model is estimated for the full sample period and the two sub-periods. The ability of the factors to explain the returns of a time series momentum strategy is assessed based upon the magnitude and statistical significance of the respective regression co-efficient. A statistically significant regression coefficient is evidence of a relationship between the returns of time series momentum and economic conditions.

The results for the linear factor model are presented in Table 6.

[18] To correct for long term trends in our extended sample period, the dividend yield factor (DIV) is measured relative to the lagged five year moving average and the short term rate (RREL) is calculated as a quotient rather than a difference.

[Insert Table 6 here]

The table lists the factors and their corresponding *t*-statistics. Consistent with Moskowitz *et al.* (2012), the linear model provides little explanatory power for time series momentum at the portfolio or sub-portfolio level. Only four, of forty, coefficients are statistically significant. The market return factor (MKT) is significant for Equity and Bond portfolios and the short term rate (RREL) is significant for both the Equity and FX portfolios. At the diversified portfolio level, there is no statistically significant explanatory factor. The inability of a linear economic factor model to explain returns is reflected in the low values reported for the adjusted R^2 measure, which range from 0.12% to 1.40%.

5.2 Conditional factor model

The explanatory power of a conditional model can vary considerably from the unconditional (linear) specification (Griffin *et al.* (2003)), consequently we define a conditional test based on the methodology used in Chordia and Shivakumar (2002) and Griffin *et al.* (2003).

To allow for a time varying relationship between the time series momentum excess returns and the macroeconomic factors, at each month, we estimate, using the current month and prior 59 months, equation (7).[19]

$$r_t^{tf} = \beta_0 + \sum_{n=1}^{N} \beta_n EF_{t-1}^{n} + \varepsilon_t \quad (7)$$

Where EF_t^n is the value of economic factor *n* at time *t*. *N* is the total number of explanatory variables (economic factors) and r_t^{tf} is the return of the time series momentum portfolio in time period *t*. We utilise a minimum of 60 months of data for our regressions and

[19] We use a 60 month estimation period for the conditional model and portfolio study consistent with the cross sectional momentum literature (Chordia and Shivakumar (2002)). In unreported analyses, we alternately use a 36 and 84 month estimation period. The results are very similar to those reported.

the t-statistics are based on Newey-West serial correlation consistent standard errors, since the rolling regressions are subject to autocorrelation in the estimates. If the economic factors fail to fully explain the returns from time series momentum, the intercept of the regression model will be positive and statistically significant.

In Table 7 we report the results of estimating a conditional model which allows for time variation - the average coefficients from the rolling five year lagged regressions and their statistical significance. Unlike the unconditional model, six of the eight macroeconomic factors have statistically significant coefficients for the full sample. This evidence highlights that the conditional implementation of the model has some explanatory power for time series momentum returns.

[Insert Table 7 here]

However, it is also noteworthy that the intercept for the model is positive and statistically significant in all three of the periods, consistent with time series momentum returns not being fully explained by the economic model. Later we investigate what portion of returns is attributable to macroeconomic risk exposure.

5.3 Time series momentum and traditional asset classes

To highlight the time varying nature of the risk exposure of the time series momentum portfolios we show the return series of time series momentum, the relationship (beta) between these series and equity and bond markets in Figure 2. The excess total return of the S&P 500 Index is used to represent the equity market, while the excess total return of the 10 Year US Treasury Bond at constant maturity is used as a proxy for the bond market. Each graph displays three data series; the mean monthly return of the market factor over the prior sixty months, the mean monthly return of the time series momentum portfolio over the same period, and the beta of the time series momentum portfolio estimated relative to the relevant financial market, again over the prior sixty months.

[Insert Figure 2 here]

Panel A shows the relationship between the diversified time series momentum portfolio and the equity market. Over the full period, the five year returns of the equity market are generally positive, and during this period the beta of the diversified portfolio is on average positive, reaching a maximum value of 0.75. The periods of negative beta, running approximately from 1970 to 1985 correspond to a poor period of performance for the equity market, where the return is lower than average and negative for a five year period around 1975. Two periods of negative beta occur after 2000 and coincide with falling equity markets in the periods following the collapse of the dotcom bubble and the failure of Lehman Brothers. Examining the relationship between the equity time series momentum portfolio and the equity market (Panel C) produces a very similar pattern; positive betas when equity markets are rising and negative betas when they are falling.

A similar analysis for the bond market is reported in Panel B and D. The excess return of the bond market can be divided into two distinct periods split by the peak of the great inflation in 1982. In the first period, bonds have a flat to small negative excess total return. Since then the excess returns of bonds have been consistently positive. Strikingly, the returns of the time series momentum portfolios are positive across all bond market conditions. In the early period, both the global and bond time series momentum portfolios have a significant negative relationship (beta) with the bond market excess return. In the later sub-period when bond returns are positive the portfolio beta is also positive. This provides evidence that time series momentum is profitable in rising and falling interest rate environments.

6.0 Momentum and asset-specific returns

Returns to the cross sectional momentum strategy have been shown to be primarily due to the component of individual equity returns explained by macroeconomic factors (Chordia and Shivakumar (2002)). This is important as it shows that the returns to cross sectional momentum are in large part due to exposure to macroeconomic risk. In order to examine if this is also the case for time series momentum, we create two alternative time series momentum portfolios based on the decomposition of asset returns into a macroeconomic factor-related component (factor-related returns) and an idiosyncratic component specific to the individual asset (asset-specific returns).

This decomposition produces two return series, factor-related and asset-specific, for each instrument. Each series is used as the basis for the creation of a set of time series momentum portfolios using the methodology described above.

The factor-related time series momentum strategy generates a trading signal for each futures contract from its factor-related return, whereas the asset-specific time series momentum portfolio is built using a signal generated from the component of each futures contract return not explained by the factor model.

The first step in this process is to decompose the returns of each futures contract into factor-related and asset-specific components. We define the regression model to explain the factor-related price movement following Grundy and Martin (2001) and Chordia and Shivakumar (2002). The model is estimated for each futures contract for each month, using the current month and prior 59 months' returns. Estimating the model using a rolling regression allows us to identify the time varying factor-related return.

$$r_t^i = \beta_{0,t} + \sum_{n=1}^{N} \beta_{n,t} \Delta F_t^n + \varepsilon_t \tag{8}$$

Where r_t^i is the excess return of futures contract *i* in time period *t*, ΔF_t^n is the change in factor *n* in time period *t* and ε_t is the error term. The model has *N* factors. The regression coefficients $\beta_{0,t}$ and $\beta_{n,t}$ are the coefficients for the model estimated over the period *t-59* to *t*, where $\beta_{0,t}$ is the regression intercept and $\beta_{n,t}$ is the regression coefficient for factor *n*.

The factor-related return of each instrument at time *t* is then estimated as

$$frr_t^i = \beta_{0,t} + \sum_{n=1}^{N} \beta_{n,t} \Delta F_t^n \tag{9}$$

Where frr_t^i is the factor-related return of instrument *i*, at time *t*. The corresponding asset-specific return, asr_t^i, is then calculated as the difference between the excess return and factor-related return at time *t*.

$$asr_t^i = r_t^i - frr_t^i \tag{10}$$

We then form two alternative time series momentum portfolios using, alternately, factor-related returns and asset-specific returns (rather than raw excess returns) to generate the trading signal.

Under this construction, if time series momentum returns are entirely due to exposure to macroeconomic risk then only the portfolios formed on factor-related returns should yield positive payoffs. The cumulative returns are reported in Figure 3 and the summary statistics of the different portfolios are displayed in Table 8.[20]

[Insert Figure 3 here]

Looking first at the diversified portfolio, it can be seen that statistically significant excess returns are generated by both sets of portfolios, factor-related (Panel B) and asset-

[20] Results are reported from January 1956 as we use a 60 month period to decompose futures returns and a further 12 month formation period for the initial time series momentum signals.

specific (Panel C) futures returns over the full sample period and both sub-periods.[21] Over the full period, the portfolio formed on asset-specific returns generates an annual excess return of 9.92% compared to 5.74% for the portfolio formed on factor-related returns. Looking at the results over the two sub-periods, the portfolio formed on macroeconomic factor-related returns is consistent, with payoffs of 5.18% and 6.13% respectively. The asset-specific return portfolio shows a different pattern, with an excess return of 14.14% in the earlier period and 7.09% since 1980.

[Insert Table 8 here]

For individual markets, all the sub-portfolios have positive returns for the asset-specific return portfolios and in all but two cases these are statistically significant. The factor-related portfolio returns are quite different. While the equity and bond portfolios produce statistically positive returns over the full period, the FX return is only marginally positive and the commodity return is close to zero. Results are more mixed over the sub-periods where, while the majority of the returns are positive, only two are statistically significant.

7.0 Economic uncertainty

Recent evidence on time series momentum has highlighted that the performance of the strategy tends to be below average for an extended period following financial crises (Hutchinson and O'Brien (2014)). Separately Bali *et al.* (2014) present evidence that economic uncertainty plays a role in explaining the cross sectional deviation in the performance of hedge funds. In order to identify if macroeconomic uncertainty is the transmission mechanism linking macroeconomic factors and the results of Hutchinson and O'Brien (2014) we specify a model of economic uncertainty, based on Bali *et al.* (2014),

[21] The signal generating process of the portfolios is quite different reflected in a full sample correlation coefficient of -0.06 for the diversified portfolios formed on factor and idiosyncratic returns.

where the time varying conditional volatility of a set of eight economic variables is used as a proxy for economic uncertainty.

Bali *et al.* (2014) define economic uncertainty as being a function of the time varying conditional volatility of the eight risk factors. The time varying conditional volatility is estimated using a vector auto regressive process to model the economic variables and a GARCH model to capture the asymmetric response of volatility to change in the economy. The auto regressive model is given as:

$$[Z_t] = [\beta_0] + [\beta_n][Z_{t-1}] + [\varepsilon_t] \tag{11}$$

Where $[Z_t]$ is an 8x1 matrix of the values of the eight variables at time *t*. $[\beta_0]$ is an 8x1 matrix of regression constants and $[\beta_n]$ is an 8x8 matrix of regression coefficients. $[\varepsilon_t]$ is the matrix of regression errors at time *t*. After regressing the model over the time period January 1950 to September 2014, the expected volatility of each factor is estimated using a multivariate asymmetric GARCH model, specifically the Threshold-GARCH (TGARCH) model of Glosten *et al.* (1993). The asymmetry allows different responses to positive and negative shocks to be modelled. The TGARCH model is:

$$E\left[\varepsilon_{i,t}^2\right] \equiv \sigma_{i,t}^2 = \gamma_0^i + \gamma_1^i \varepsilon_{t-1}^2 + \gamma_2^i \sigma_{t-1}^2 + \gamma_3^i \varepsilon_{t-1}^2 D_{i,t-1} \tag{12}$$

$$D_{1,t} = 1 \ \ for\ \varepsilon_{i,t} < 0, 0\ otherwise$$

Where $E\left[\varepsilon_{i,t}^2\right]$ is the expected value of the square of the error term of variable *i*, at time *t*. This is the conditional volatility $\sigma_{i,t}^2$, of the instrument. γ_n^i is the coefficient *n* of variable *i*. $D_{i,t}$ is a dummy variable set to one for $\varepsilon_{i,t} < 0$ or zero otherwise. A positive value for γ_3^i indicates negative shocks cause higher volatility than positive shocks.

The final stage of the process combines the volatilities of the eight factors to generate an index of economic uncertainty. The volatilities of the factors are both persistent and cross correlated, allowing the use of principle component analysis. Following Bali *et al.* (2014) we use the first principle component to generate a linear function of the eight individual time series.

Our methodology differs from Bali *et al.* (2014) in two ways. Bali *et al.* (2014) use a recursive estimation procedure, whereas we use a single estimation for the full time period, which induces a look-ahead bias. The advantage of our approach is that it allows us to begin our analysis in 1950, maximising the sample of available economic data.[22] While Bali *et al.* (2014) estimate all parameters simultaneously, we estimate the economic model separately from the T-GARCH volatility model.

The economic uncertainty index based on Bali *et al.* (2014) is reported in Figure 4. The measure varies through time, but peak economic uncertainty measured by the model closely corresponds to the financial crises identified in Hutchinson and O'Brien (2014).

[Insert Figure 4 here]

To see the impact of economic uncertainty on the performance of time series momentum, we compare the performance in periods of high and low uncertainty over the full period and each of the sub-periods. The markets are defined as high or low uncertainty by comparing the level of economic uncertainty with its mean for the period.[23] [24] The results are shown in Table 9.

[22] The recursive estimation approach requires an extended window of data, prior to the sample period (Bali *et al.* (2014) use 23 years). As our economic data set begins in 1950, incorporating a similar formation period eliminates much of the first sub-sample period.
[23] As the mean uncertainty is a function of the sub-period, individual months can be assigned to different states depending on the mean of the period under investigation.
[24] Results are very similar when the analysis is based on the median of the series.

[Insert Table 9 here]

The diversified portfolio exhibits better performance in periods of below average uncertainty for both the full sample period (18.39% against 9.84%) and both sub-periods, (17.48% compared with 14.34% in the earlier period and 17.33% compared with 9.92% in the later period). This pattern is evident in the equity and currency markets, over both the full period and both sub-periods; although it should be noted the sample size for currencies is small in the earlier period, running from 1972 to 1979.

The results for government bonds and commodities are less consistent. The performance of the bond portfolio over the full period is marginally better when economic uncertainty is reduced, while it performs better in low uncertainty conditions in the earlier period and high uncertainty conditions in the later sub-period. The commodity portfolio again shows a different pattern, with similar performance under high and low uncertainty over the full periods and performing better in high uncertainty conditions in the first sub-period.

In order to further investigate the relationship between the returns and economic uncertainty a series of regressions were carried out based on the model

$$r_t^{tf} = \beta_o + \beta_1 U_{t-l} + \varepsilon_t \tag{13}$$

Where r_t^{tf} is the return of the diversified time series momentum portfolio at time t, and U_{t-l} is the value of the economic uncertainty index at time t - l. The variable l is the measure of the lag or lead of the uncertainty index relative to the return series. The test statistics of the regression coefficients for a range of values of l (-18 to 18) is displayed in Figure 5.

[Insert Figure 5 here]

Figure 5 shows a statistically significant negative relationship between the returns to time series momentum and the uncertainty index in the contemporaneous month and for lags of up to six months. Following periods when economic uncertainty is low (high) the returns of the time series momentum strategy are higher (lower) than average. Given the association of economic uncertainty and periods following financial crises, this helps explain previous findings that time series momentum returns are below average in the period after financial crises (Hutchinson and O'Brien (2014)).

8. Conclusions

This article was motivated by two observations. First, CTAs have received large inflows of capital following the 2008 financial crisis. Second, investors' motivation for allocating to CTAs is often due to an expectation of performance in equity bear markets, without a consideration of performance in other market states, or the drivers of performance. We have shown that the returns to time series momentum are connected to the business cycle. Time series momentum earns positive returns in both expansions and recessions but the returns are especially strong in expansions. Whether we measure the business cycle using NBER data, GDP data or use interest rate spreads as proxies for short and long term fluctuations, our results are consistent. Returns are statistically significantly higher by between 5% and 8% in expansions. These findings dispel the notion that high returns to time series momentum are specific to equity market states.

Taken together our results provide a degree of clarity on the return drivers of time series momentum. Complementing Moskowitz *et al.* (2012) who document a behavioural driver, we find that there is a role for rational price theories to explain a portion of time series momentum profitability. We find that the returns are related to a set of macroeconomic factors that have been shown in the literature to be important in explaining the returns of traditional asset classes and hedge funds. Our results indicate that about 40 percent of the returns of time series momentum are due to time varying exposure to these macroeconomic variables, which are related to the business cycle. These findings are consistent with the conclusions of Chordia and Shivakumar (2002) for cross sectional momentum, that a portion of the profitability of momentum strategies represents compensation for bearing time varying risk, consistent with rational asset pricing theories.

Finally, we note the interesting finding that the performance of time series momentum improves when economic uncertainty is diminished. This result provides a link between the finding of Hutchinson and O'Brien (2014), that time series momentum tends to perform less well than average following periods of financial crisis, and changes in the business cycle. Using a new methodology, we document that uncertainty is the transmission mechanism linking changes in the macroeconomic variables and changes in the performance of time series momentum following financial crisis.

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Appendix A: Data Sources

A.1 Equity indices

The universe of equity indices has twenty components. Fourteen of these consist of data from developed markets, with future prices available from Datastream starting at various dates from January 1980 and derived forward prices generated from data provided by Global Financial Data prior to that. In each case Global Financial Data provides a total return index, which allows the yield to be calculated. This group consists of Australia (SPI200), Canada (TSX 60), Netherlands (AEX), France (CAC 40), Germany (DAX), Hong Kong (Hang Seng), Korea (KOSPI 200), Japan (Nikkei 225), United States (S&P 500), United Kingdom (FTSE 100), Spain (IBES 35), Italy (MIB), Sweden (OMX 30) and Switzerland (SMI).

The six additional indices are the three mid cap indices (Germany, Switzerland and United States) and three alternative indices for the US (Dow Jones, Russell 2000 and NASDAQ 100). We only include exchange traded future contract data for these indices.

A.2 Bond indices

A total of thirteen government bond indices from six countries are used. Australia (10 and 3 year), Canada (10 year), United States (2, 5, 10 and 30 year), Germany (2 ,5, 10 and 30 year), Japan (10 year) and United Kingdom (10 year). Exchange data for these is from Datastream, starting on a variety of dates from January 1980. Data for eight of these is extended backwards using total return indices and short term yields from Global Financial Data.

A.3 Currencies

The universe of currency forwards consists of ten currencies. Forwards are created for all currency pairs from spot data and short term interest rates. The spot rates are sources from

Datastream/MSCI from 1980 and, prior to that, from Global Financial Data. Although data is available back to 1920, currencies are only considered for inclusion and statistics provided from the end of the Bretton-Woods fixed rate system in 1971. The Euro and German Mark are spliced into one time series. The currencies included are Australia, Canada, Euro (Germany), Norway, New Zealand, Sweden, Switzerland, United Kingdom and United States.

A.4 Commodities

Twenty one commodities are included; Copper, Gold and Silver (COMEX), Light Crude Oil, Natural Gas, NY Heating Oil, Palladium, Platinum and RBOB Gasoline (NYMEX), Cocoa, Coffee, Cotton, Gas Oil and Sugar (ICE), Corn, Soya Bean Oil, Soya Bean Meal, Soya Beans and Wheat (CME) and Lean Hogs and Live Cattle (CBOT). The commodity data is entirely based on prices of exchange traded futures. As cost of carry data is unavailable it is not possible to accurately estimate forward prices prior to the availability of exchange traded futures. The commodity data from 1980 was sourced from DataStream while the earlier data was sourced from Commodity Systems Inc. (CSI). The Copper contract consists of a combination of the medium grade copper contract traded until l988 and the high grade copper contract traded since then, sourced from CSI and DataStream respectively.

A.5 Risk free rates

Short term interest rates are sourced from Global Financial Data due to more extensive coverage. The one month interbank rate (LIBOR or equivalent) is the preferred rate. When this is not available, the closest available interbank rate was used, and finally the central bank base rate.

A.6 Economic factor model

Table 10 shows the data sources used for the primary data used to define the economic factor model. All data is available from January 1950, with the exception of the yield of the 10 Year US Treasury Bond (constant maturity), which becomes available from 1952. The first two years of this time series were back filled using the US 10 Year Treasury Bond Yield from the same source.

[Insert Table 10 here]

Figure 1
Performance of the Diversified Time Series Momentum Portfolio

The figure shows the natural logarithm of the cumulative excess return series of a diversified time series momentum portfolio from January 1950 to September 2014. Excess returns are presented net of transaction costs and gross of fees.

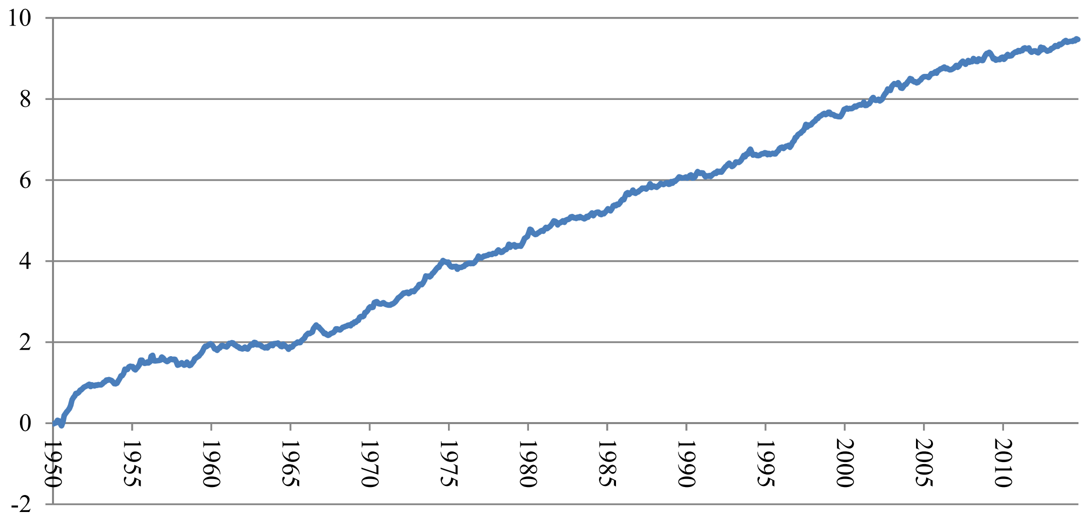
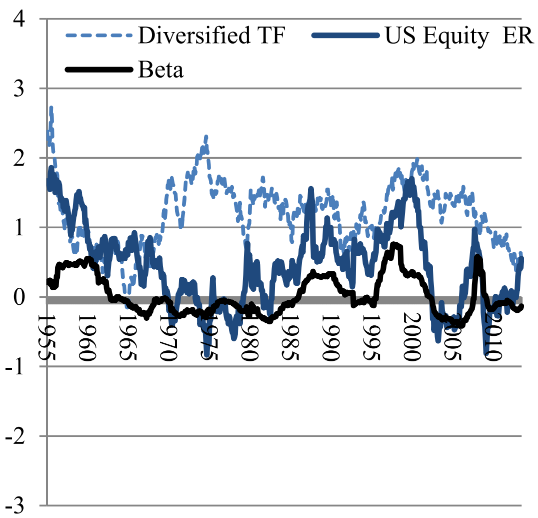


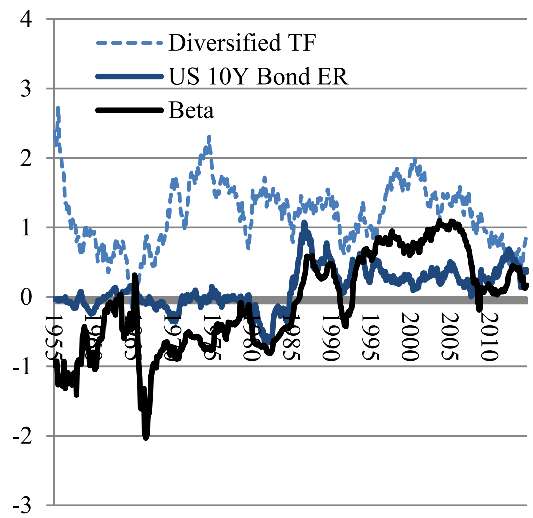
Figure 2
Rolling Beta of Time Series Momentum for Financial Markets

Each panel presents the average five year monthly total excess return of a time series momentum portfolio, the average five year monthly total excess return of an asset and the beta between the two. Panel A presents the returns of the US equity market and the diversified time series momentum portfolio. Panel B presents the returns of US Treasury bonds and the diversified time series momentum portfolio. Panel C presents the returns of the US equity market and the equity index time series momentum portfolio. Panel D presents the returns of US Treasury bonds and the government bond time series momentum portfolio. Results are presented from January 1955 to September 2014.

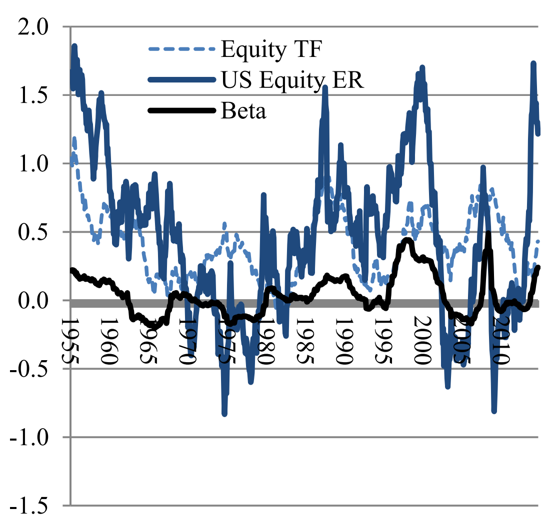
Panel A: Diversified Time Series Momentum & Equity Market



Panel B: Diversified Time Series Momentum & Bond Market



Panel C: Equity Time Series Momentum & Equity Market



Panel D: Bond Time Series Momentum & Bond Market

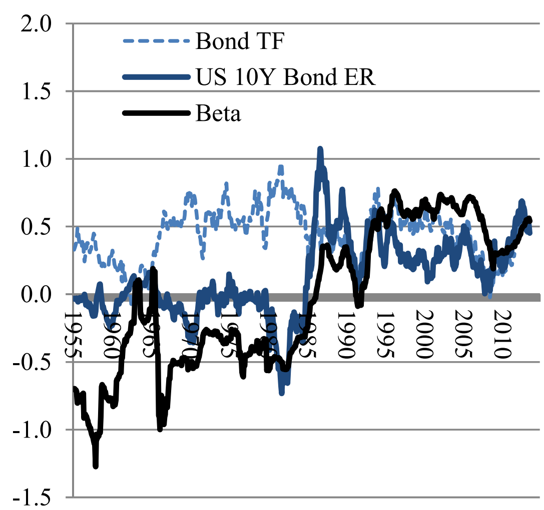


Figure 3
Portfolio Formed on Explained and Unexplained Returns

The figure shows the natural logarithm of the cumulative excess return series of two global diversified time series momentum portfolio from January 1956 to September 2014. Portfolio Formed on Explained Returns is a time series momentum portfolio formed from signals based on the return of the underlying instruments explained by the macroeconomic model. Portfolio Formed on Unexplained Returns is a time series momentum portfolio formed from signals based on the unexplained (futures specific) return of the underlying instruments.

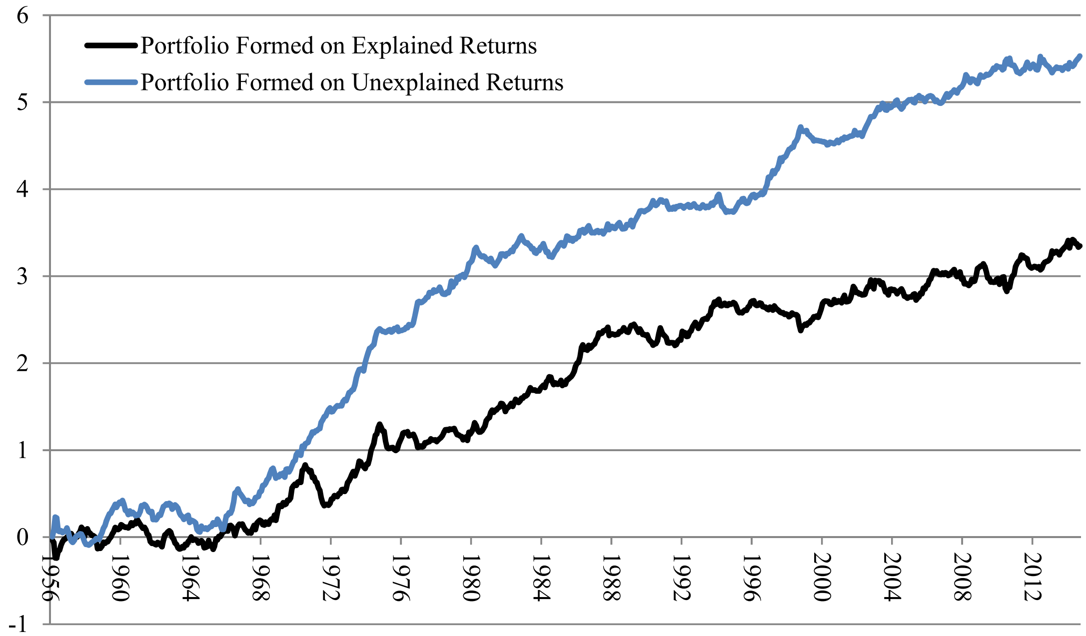


Figure 4
Economic Uncertainty Index

The figure presents the measure of economic uncertainty used in this paper. The measure is based on the methodology defined in Bali *et al.* (2014). The major peaks, associated with the periods of highest uncertainty, are identified. The labels correspond to the financial crises identified in Hutchinson and O'Brien (2014). The times series runs from January 1950 to September 2014.

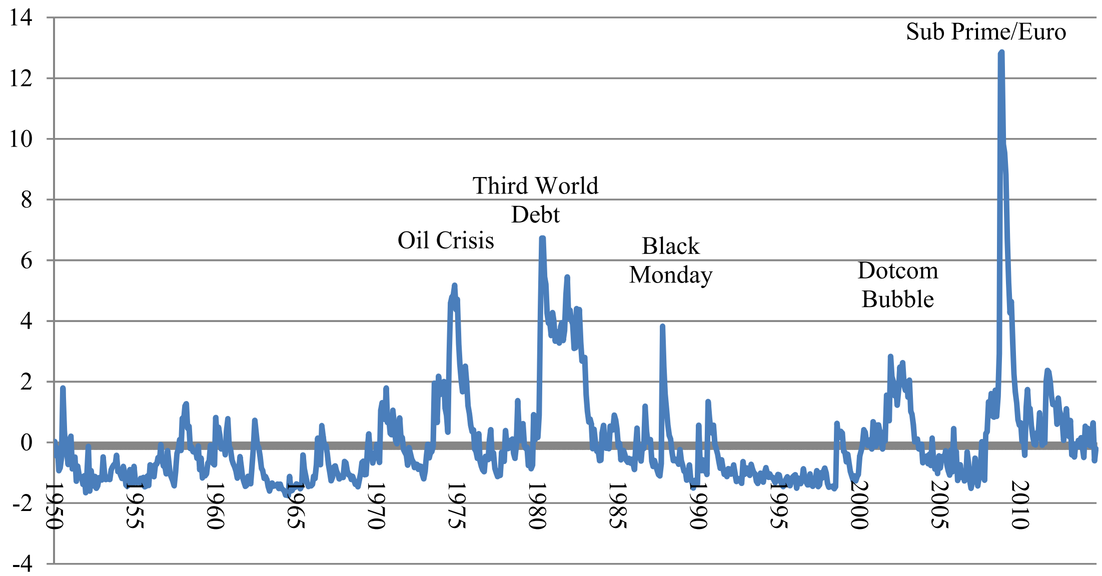


Figure 5
Time Series Momentum Returns and Economic Uncertainty

The excess returns of the diversified time series momentum portfolio was regressed against the Economic Uncertainty Index at a variety of lags/leads using the regression model $r_t^{tf} = \beta_o + \beta_1 U_{t-l} + \varepsilon_t$, where U_t is the value of the economic uncertainty index at time t and l is the lag (lead), ranging from -18 to +18 months. The figure displays the test statistics of the regression coefficient β_1. The results of the lagged index appear to the left, and the lead index to the right. The times series run from January 1950 to September 2014.

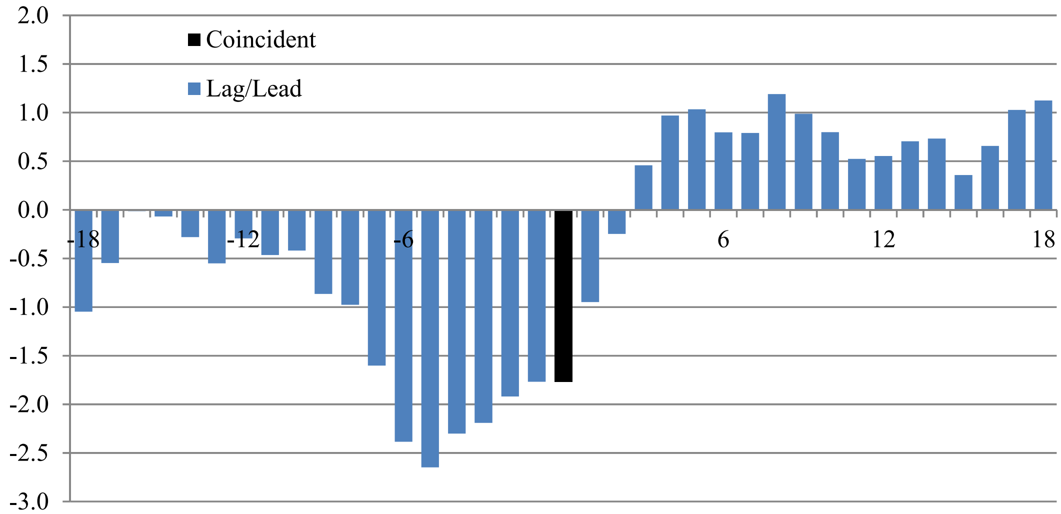


Table 1
Future Contracts

The table provides a list of the underlying futures contracts used to create the time series momentum portfolios used in this study. Each future is listed with its average annual excess return, volatility and the date the return series becomes available. The futures are divided into four classes; Commodities, Government Bonds, Equity Indices and currencies. All data series end in September 2014.

	Start Date	Annual Return	Annual Vol.		Start Date	Annual Return	Annual Vol.
Commodity Futures				**Equity Index Futures**			
COCOA	Jan-66	-0.48	28.56	SPI 200 - Australia	Jan-50	3.78	17.01
COFFEE	Sep-72	-1.47	37.87	S&P TSX60- Canada	Jan-70	3.19	16.42
COPPER	Jan-66	4.23	27.51	Dow Jones-US	Oct-77	4.12	15.28
CORN	Aug-50	-3.24	22.26	NASDAQ 100 - US	Apr-96	8.18	27.29
COTTON	Apr-67	-0.83	25.39	AEX - Netherlands	Jan-70	5.02	18.91
GAS OIL	Sep-03	9.78	28.87	CAC 40 France	Jan-70	3.36	20.26
GOLD	Feb-75	3.97	19.97	DAX - Germany	Jan-50	5.82	18.50
LEAN HOGS	Mar-66	2.94	26.05	MDAX -Germany	Mar-05	11.14	21.36
LIGHT CRUDE OIL	Mar-83	6.14	33.96	HANG SENG - Hong Kong	Jan-70	10.53	33.29
LIVE CATTLE	Dec-64	4.31	16.91	S&P Midcap- US	Feb-92	8.19	16.78
NATURAL GAS	Apr-90	-10.76	56.64	NIKKIE 225 - Japan	Jan-50	6.08	20.30
NY HEATING OIL	Jan-80	6.12	31.97	S&P 500 – US	Jan-50	5.48	14.52
PALLADIUM	Feb-77	5.75	35.08	KOSPI 200 - Korea	Jan-65	8.86	27.38
PLATINUM	Feb-64	2.99	26.91	FTSE 100- UK	Jan-50	5.05	17.90
RBOB GASOLINE	Oct-05	6.20	32.28	IBEX 35 - Spain	Jan-70	1.68	20.85
SILVER	Jul-73	-0.51	31.00	MIB – Italy	Jan-50	2.11	21.95
SOYABEAN MEAL	Sep-51	3.57	28.69	Russell 2000 - US	Aug-07	6.09	21.91
SOYABEAN OIL	Aug-50	6.84	27.79	OMXS 30 - Sweden	Jan-70	6.77	21.93
SOYABEANS	Aug-50	3.31	24.02	SMI - Switzerland	Jan-70	5.39	16.45
SUGAR	Jan-66	-2.99	40.52	SMI Midcap - Switzerland	Sep-05	6.17	17.47
WHEAT	Aug-50	-4.09	23.14				
Bond Futures				**Currency Forwards**			
Australia-10Y	Jan-50	0.50	6.73	AUD/USD	Aug-71	-1.69	11.51
Australia-3Y	May-88	4.03	9.47	CAD/USD	Aug-71	-0.39	6.54
Canada-10Y	Jan-50	1.29	6.22	CHF/USD	Aug-71	-0.80	12.23
US-5Y	Jan-50	0.82	4.98	EUR/USD*	Aug-71	0.11	10.91
US-2Y	Jun-90	1.62	1.68	GBP/USD	Aug-71	-0.77	10.15
US-10Y	Jan-50	1.21	6.75	JPY/USD	Aug-71	-0.14	11.18
US-30Y	Jan-50	0.78	9.77	NOK/USD	Aug-71	-1.36	10.58
Germany-5Y	Oct-91	2.97	3.22	NZD/USD	Aug-71	-1.97	12.41
Germany-30Y	Sep-05	5.34	11.88	SEK/USD	Aug-71	0.05	11.03
Germany-2Y	Mar-97	0.92	1.32				
Germany-10Y	Jan-50	2.33	5.05				
Japan-10Y	Jan-50	2.67	6.15				
UK-10Y	Jan-50	1.21	8.27				

* DEM/USD prior to the introduction of the Euro in Jan 1999

Table 2
Performance of Time Series Momentum Portfolios

The table reports the average annualised excess return and volatility of five time series momentum portfolios, comprising of a diversified portfolio and four asset class sub-portfolios; equity indices (Equity), government bonds (Bonds), currencies (FX) and commodities (Commodity). The results are presented from January 1950 to September 2014 and over two sub-periods, January 1950 to December 1979 and January 1980 to September 2014. The FX and Commodity time series begin in August 1972 and August 1951, respectively. All other series begin in January 1950. Excess returns are presented net of transaction costs and gross of fees.

		Diversified	Equity	Bonds	FX	Commodity
1950-2014	Return (%)	15.75	5.18	5.29	1.81	2.04
	Vol. (%)	12.55	5.41	6.39	4.45	4.17
1950-1979	Return (%)	16.60	5.03	5.46	2.46	1.55
	Vol. (%)	13.01	4.97	6.26	5.91	5.00
1980-2014	Return	15.03	5.30	5.15	1.67	2.45
	Vol. (%)	12.14	5.77	6.50	4.08	3.34

Table 3
The Performance of the Time Series Momentum through the Economic Cycle

The table presents the average annualised excess return of the time series momentum strategies in periods of economic expansion (Exp.) and recession (Rec.). Panel A presents the results based on the NBER definition of economic cycles, while Panel B presents results based on changes in GDP. The first row of each panel (% Time) displays the proportion of the sample period that the economy was in expansion or recession. Results are presented for a diversified portfolio and four asset-specific sub-portfolios; equity indices, government bonds, FX and commodities. The results are presented from January 1950 to September 2014 and over two sub-periods, January 1950 to December 1979 and January 1980 to September 2014. The FX and commodity time series begin in August 1972 and August 1951, respectively. All other series begin in January 1950. Excess returns are presented net of transaction costs and gross of fees. Statistically significant differences, calculated using a one tailed test, are indicated at confidence levels of 10% (*), 5% (**) and 1% (***).

	1950-1979		1980-2014			1950-2014		
	Exp.	Rec.	Exp.	Rec.		Exp.	Rec.	
Panel A: NBER Economic Cycles								
% Time	84.72	15.28	86.57	13.43		85.71	14.29	
Equity	5.53	2.31	5.84	2.17		5.70	2.24	*
Bonds	5.60	5.05	5.75	2.02		5.68	3.52	
FX	4.01	-3.80	2.39	-2.43	***	2.66	-2.74	***
Commodity	1.47	2.68	2.17	4.47		1.86	3.58	
Diversified	17.37	10.25	16.14	6.22	*	16.71	8.22	**
Panel B: GDP Data								
% Time	84.17	15.83	87.77	12.23		86.10	13.90	
Equity	5.54	2.37	5.67	3.00		5.61	2.67	*
Bonds	5.51	5.57	5.99	-0.06	**	5.77	2.91	
FX	3.67	-2.67	2.11	-0.86	*	2.37	-1.27	**
Commodity	1.48	2.57	2.32	3.59		1.95	3.05	
Diversified	17.10	11.93	16.08	5.67	*	16.55	8.97	**

Table 4
The Performance of Time Series Momentum in Short Term and Long Term Business Cycle Expansions and Contractions

The table presents the average annualised excess return of the time series momentum strategies at different stages of the market cycle, based on interest rate spreads. In each case, a month is defined as high (low) if the value of the spread for that month is greater (less) than the average value for the sample period. The average return for high (low) periods is the annualized mean of the excess return in all high (low) spread periods. Panel A presents the results based on the term spread of interest rates (US 10Y T-Bond Yield – 3M US T-Bill Yield). Panel B presents the results based on the default spread of interests rates (US BAA Corporate Bond Yield – US AAA Corporate Bond Yield). The first row of each panel (% Time) displays the proportion of the sample period that the spread was above (below) the average for the period. Results are presented for a diversified portfolio and four asset class sub-portfolios; equity indices, government bonds, FX and commodities. The results are presented from January 1950 to June 2013 and over two sub-periods, January 1950 to December 1979 and January 1980 to September 2014. The FX and commodity time series begin in August 1972 and August 1951, respectively. All other series begin in January 1950. Excess returns are presented net of transaction costs and gross of fees. Statistically significant differences, calculated using a one tailed test, are indicated at confidence levels of 10% (*), 5% (**) and 1% (***).

	1950-1979			1980-2014			1950-2014		
	High	Low		High	Low		High	Low	
Panel A: Term Spread									
% Time	47.78	52.22		53.00	47.00		48.01	51.99	
Equity	5.60	4.53		4.57	6.22		4.28	6.05	*
Bonds	3.03	7.79	***	4.82	5.72		4.27	6.39	*
FX	2.22	3.07		0.27	3.41	***	0.86	3.15	
Commodity	1.22	2.09		1.93	3.09		2.36	1.87	
Diversified	13.33	18.98		11.59	18.44	**	11.95	18.76	***
Panel B: Default Spread									
% Time	34.17	65.83		42.69	57.31		45.56	54.44	
Equity	3.12	6.04	**	4.53	5.95		4.30	5.96	
Bonds	1.36	7.67	***	5.30	5.21		5.18	5.53	
FX	3.57	1.91		0.75	2.49		1.03	2.55	
Commodity	3.71	0.58	**	2.26	2.64		2.46	1.82	
Diversified	9.59	19.76	***	12.84	16.28		12.69	17.84	**

Table 5
Macroeconomic Risk Model Factor Definitions

The table presents the definitions of the eight economic factors that make up the economic model used in this study, based on the economic uncertainty model of Bali *et al.* (2014). The first column shows the factor name as used in Bali *et al.* (2014) and the second column defines the factor in terms of the underlying economic time series.

Factor	Definition
DEF	The default spread, the difference between BAA and AAA rated US corporate bonds
DIV	The aggregate dividend yield on the S&P 500
GDP	The monthly change in US GDP per capita
INF	Monthly inflation based on US CPI
MKT	The excess return on a value weight index of all US stocks (CRSP Universe)
RREL	The 3-month US T-Bill rate divided by its 12 month moving average
TERM	The term spread, the difference between 10 Year and 3 Month US Treasury rates
UNEMP	The total number unemployed divided by labour force.

Table 6
Linear Regression Factor Model

The table presents the results of regressing the excess returns of five time series momentum portfolios; a diversified portfolio and four asset class sub-portfolios on the economic factor model. The table presents the regression coefficients and associated test statistics from the regression model $r_t^{tf} = \beta_0 + \beta_1 DEF_t + \beta_2 DIV_t + \beta_3 GDP_t + \beta_4 INF_t + \beta_5 MKT_t + \beta_6 RREL_t + \beta_7 TERM_t + \beta_8 UNEMP_t + \varepsilon_t$. Regressions are estimated from January 1950 to September 2014 for the diversified portfolio and the equity and bond sub-portfolios. The FX and commodity regressions are from August 1972 to September 2014 and August 1951 to September 2014, respectively. Coefficients significant at the 5% level are highlighted in bold. The adjusted R^2 are presented for each regression.

	INT	DEF	DIV	GDP	INF	MKT	RREL	TERM	UNEMP	Adj. R^2
Equity	**0.0070**	-0.0002	-0.0017	0.0009	-0.0017	**0.0003**	**0.0047**	0.0005	-0.0005	0.0140
	3.12	-0.12	-0.50	0.47	-1.01	**2.59**	**2.08**	0.81	-0.99	
Bond	0.0052	-0.0037	0.0030	0.0000	-0.0018	**-0.0004**	-0.0010	-0.0013	0.0010	0.0043
	1.94	-1.64	0.75	-0.02	-0.91	**-2.37**	-0.37	-1.69	1.49	
FX	0.0048	0.0008	0.0013	0.0031	-0.0032	0.0000	**0.0042**	-0.0003	-0.0004	0.0057
	1.80	0.46	0.40	1.29	-1.89	0.00	**1.96**	-0.43	-0.81	
Commodity	0.0025	0.0008	-0.0022	-0.0021	0.0036	-0.0001	-0.0005	0.0004	-0.0005	0.0049
	1.41	0.54	-0.80	-1.33	2.70	-0.61	-0.28	0.73	-1.14	
Diversified	**0.0218**	-0.0031	0.0041	0.0018	-0.0011	0.0000	0.0071	-0.0001	-0.0009	0.0012
	4.17	-0.71	0.52	0.40	-0.29	-0.01	1.35	-0.08	-0.75	

Table 7
Time Varying Regression Model

This table shows the average value of the time varying regression coefficients when the excess returns of a diversified time series momentum portfolio are regressed against the lagged economic model using $r_t^{tf} = \beta_0 + \beta_1 DEF_{t-1} + \beta_2 DIV_{t-1} + \beta_3 GDP_{t-1} + \beta_4 INF_{t-1} + \beta_5 MKT_{t-1} + \beta_6 RREL_{t-1} + \beta_7 TERM_{t-1} + \beta_8 UNEMP_{t-1} + \varepsilon_t$ over a sixty month window. The reported coefficient t-statistics are corrected for serial correlation in the error term using the Newey-West autocorrelation consistent errors. Significant coefficients (5% level) are shown in bold. Results are presented from January 1955 to September 2014 and for two sub-periods, January 1955 to December 1979 and January 1980 to September 2014.

	INT	DEF	DIV	GDP	INF	MKT	RREL	TERM	UNEMP	Adj. R^2
1955 - 2014	**0.0514**	**-0.0106**	**-0.0209**	**-0.0136**	**-0.0112**	-0.0001	0.0067	**0.0038**	**-0.0047**	0.0669
	8.86	-2.34	-2.50	-2.75	-2.75	-0.33	1.24	2.50	-3.55	
1955 - 1979	**0.0406**	**-0.0319**	**-0.0395**	-0.0083	-0.0067	0.0004	0.0206	0.0050	-0.0009	0.1221
	3.45	-3.18	-2.32	-1.21	-0.91	0.84	1.71	1.29	-0.34	
1980 - 2014	**0.0596**	0.0053	-0.0068	**-0.0176**	**-0.0146**	-0.0005	-0.0037	0.0030	**-0.0076**	0.0186
	7.76	0.94	-0.58	-2.14	-2.79	-1.28	-0.60	1.63	-4.82	

Table 8
Decomposition of Time Series Momentum Returns

In each panel the average annualised excess returns and t-statistics are presented across five portfolios and three time periods. The five portfolios consist of a diversified portfolio and four asset class sub-portfolios; equity indices, government bonds, FX and commodities. The results are presented for the period from January 1956 to September 2014 and two sub-periods; January 1956 to December 1979 and January 1980 to September 2014. The FX time series begins in August 19776 and the commodity in August 1956, all others begin in January 1956. Panel A presents the results of the standard time series momentum model, where trading signals are generated from raw excess returns. Panel B shows the return statistics of time series momentum portfolios formed from signals based on the return of the underlying instruments explained by the macroeconomic model. Panel C presents the results of time series momentum portfolios formed from signals based on the asset-specific return of the underlying instruments. Excess returns significant at the 5% level are shown in bold.

	Equity	Bonds	FX	Commodity	Diversified
Panel A: Portfolios Formed on Raw Returns					
1956-2014	**4.42**	**5.42**	**1.93**	**2.23**	**14.52**
	6.41	6.53	2.97	4.41	9.04
1956-1979	**3.16**	**5.82**	4.18	**1.90**	**13.79**
	3.37	4.49	1.68	2.05	5.49
1980-2014	**5.30**	**5.15**	**1.67**	**2.45**	**15.03**
	5.46	4.76	2.52	4.37	7.19
Panel B: Portfolios Formed on Economic Factor-Related Returns					
1956-2014	**3.02**	**2.14**	0.40	-0.03	**5.74**
	4.19	2.68	0.72	0.10	3.90
1956-1979	0.34	**5.42**	-5.48	-0.53	**5.18**
	0.44	3.99	-1.64	-0.41	2.17
1980-2014	**4.92**	-0.08	1.10	0.32	**6.13**
	4.93	0.13	1.78	0.68	3.30
Panel C: Portfolios Formed on Asset-Specific Returns					
1956-2014	**2.41**	**3.73**	1.05	**1.89**	**9.92**
	4.60	4.70	1.67	3.53	6.77
1956-1979	**4.09**	**3.36**	**6.23**	**2.65**	**14.14**
	4.25	2.89	2.09	2.49	5.40
1980-2014	**1.27**	**3.98**	0.47	**1.37**	**7.09**
	2.18	3.70	0.81	2.59	4.19

Note: The FX sub-portfolio begins in 1977, and so results for 1956-1979 are based on a three year sample.

Table 9
Time Series Momentum Performance and Economic Uncertainty

The table reports the average annualised excess return for five time series momentum portfolios in periods of high and low risk. The portfolios consist of a diversified portfolio and four asset class sub-portfolios; equity indices, government bonds, FX and commodities. Uncertainty is measured using the economic uncertainty index set out in this paper based on Bali *et al.* (2014). A month is defined as high (low) risk if the value of the risk measure for that month is greater (less) than the average value for the sample period. The average return for high (low) risk periods is the mean of the excess return in all high (low) risk periods. The results are presented from January 1950 to September 2014 and over two sub-periods, January 1950 to December 1979 and January 1980 to September 2014. The FX time series begins in August 1972 and the commodity in August 1951; all others begin in January 1950. Excess returns are presented net of transaction costs and gross of fees. Statistically significant differences, calculated using a one tailed test, are indicated at confidence levels of 10% (*), 5% (**) and 1% (***).

	1950-1979			1980 – 2014			1950-2014		
	High	Low		High	Low		High	Low	
% Time	38.06	61.94		34.05	65.95		33.85	66.15	
Equity	3.66	5.89		1.46	7.35	***	2.36	6.66	***
Bonds	4.64	6.06		6.27	4.72		5.25	5.43	
FX	3.06	2.37		0.64	2.32		-0.08	2.92	**
Commodity	3.20	0.72	*	1.56	2.95		2.05	2.14	
Diversified	14.34	17.48		9.92	17.33	*	9.84	18.39	***

Table 10
Macroeconomic Risk Model: Data Sources

This table lists the sources for the data items used in the economic analyses. It includes the primary data used to derive the factors of the economic uncertainty model and the items used to define the economic cycle. All data items listed in this section are available for download from the named website.

Data Item	Source
BAA and AAA rated US Corporate Bond Yields 3-Month US T-Bill Rate 10 Year Constant Maturity US Treasury Bond	www.federalreserve.gov/releases/h15/data.htm
The Aggregate Dividend Yield on the S&P 500 US CPI	www.econ.yale.edu/~shiller/data.htm
US GDP US GDP per capita	research.stlouisfed.org/fred2/
Excess Return on US stocks	mba.tuck.dartmouth.edu/pages/faculty/ken_french/data_library.html
Unemployment Rate	www.bls.gov/cps/lfcharacteristics.htm
NBER Economic Cycles	www.nber.org/cycles/cyclesmain.html