Is this time different?

Trend following and financial crises

Mark C. Hutchinson
Department of Accounting, Finance & Information Systems
and Centre for Investment Research
University College Cork
College Road, Cork, Ireland.
Tel +353 21 490 2597
Email: m.hutchinson@ucc.ie

John O'Brien
Department of Accounting, Finance & Information Systems
and Centre for Investment Research
University College Cork
College Road, Cork, Ireland.
Tel +353 21 490 1911
Email: j.obrien@ucc.ie

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Abstract

Following large positive returns in 2008, Commodity Trading Advisors (CTAs) received increased attention and allocations from institutional investors. Subsequent performance has been below its long term average. This has occurred in a period following the largest financial crisis since the great depression. In this paper, using almost a century of data, we investigate what typically happens to the core strategy pursued by these funds in global financial crises. We also examine the time series behaviour of the markets traded by CTAs during these crisis periods. Our results show that in an extended period following financial crises trend following average returns are less than half those earned in no-crisis periods. Evidence from regional crises shows a similar pattern. We also find that futures markets do not display the strong time series return predictability prevalent in no-crisis periods, resulting in relatively weak returns for trend following strategies for, on average, four years following the start of a financial crisis.

Following strong performance in 2008 the aggregate performance of trend following Commodity Trading Advisor (CTA) funds has been relatively weak. From January 2009 to June 2013, the annualized return of the Newedge Trend Index is -0.8%, versus 8.0% over the prior five year period, while assets under management of CTAs have grown from $206 billion to $331 billion.[1] [2] This has occurred during a period of slow recovery in the US and prolonged crisis in the Eurozone.

Understandably, investors in CTAs are now beginning to question performance. Have markets changed post the 2008 financial crisis? Will these types of strategies ever work again? In this paper, using almost a century of data on trend following, we attempt to provide some guidance on these issues by empirically investigating the following research questions. Is what has happened to the performance of trend following subsequent to the US subprime and Eurozone crises typical of what happens post a financial crisis? If yes, then what happens to price patterns in the futures markets traded by these funds to cause such poor performance during such turbulent periods?

Our results indicate that subsequent to a global financial crisis trend following performance tends to be weak for four years on average. Comparing the performance of crisis and no-crisis periods, the average return in the first twenty four months following the start of a crisis is one third of the return earned in no-crisis periods, while the performance in the forty eight months after a crisis start is half that of no-crisis periods. Providing additional supporting evidence we find a similar effect when we examine portfolios formed of local assets during regional financial crises.

Looking at the changing time series dynamics of futures markets we find a breakdown in futures market return predictability during the crisis periods. In no-crisis periods futures

[1] Source: Barclayhedge.
[2] For the systematic sub-category, AUM has grown from $163 billion to $261 billion.

market returns exhibit strong serial correlation at lags of up to twelve months, whereas during crisis periods correlations are significantly reduced, and in a number of cases turn negative. This lack of time series return predictability reduces the opportunity for trend following to generate returns.

The literature on trend following 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, Miffre, and Rallis (2010) for commodities and Okunev and White (2003) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b) for currencies). Schneeweis, Kazemi, and Spurgin (2008) provide a comprehensive review. The evidence of these studies is generally positive on the performance of trend following with positive Sharpe ratios and little correlation with traditional asset classes. We provide further evidence on the long term performance of trend following strategies through an analysis of the performance of a multiple asset class portfolio.

Related literature focuses on identifying the risks faced by CTAs. In a highly cited study, Fung and Hsieh (2001) use a portfolio of options to capture the non-linear payoff from CTAs. More recent research focuses on both the longer term performance of these strategies (Hurst, Ooi, and Pedersen (2012)), identifying why futures markets trend (Moskowitz, Ooi, and Pedersen (2012)), and also examining the interaction between trend following and value (Asness, Moskowitz, and Pedersen (2013)). Our research identifies and analyses a further performance risk for investors; the poor performance of trend following subsequent to a financial crisis.

Our finding on the differing performance of trend following strategies in crisis and no-crisis periods is consistent with predictions from behavioural finance and evidence on cross sectional momentum in different economic states. Behavioural models link momentum to investor overconfidence (Daniel, Hirshleifer, and Subrahmanyam (1998)) and decreasing risk aversion (Hong and Stein (1999)), with both models leading to overreaction and return predictability in asset prices. Cooper, Gutierrez, and Hameed (2004) highlights how overconfidence should fall and risk aversion should increase following market declines. These effects lower the likelihood of overreactions, and consequently return predictability, in periods following a financial crisis under the models proposed by both Daniel et al. (1998) and Hong and Stein (1999). Cooper et al. (2004) find evidence to support both these predictions for cross sectional momentum, finding the state (direction) of the market is critically important to the profitability of cross-sectional momentum strategies.

Finally, there is an emerging literature examining the performance of dynamic trading strategies during periods of financial crisis (see for example Brunnermeier, Nagel, and Pedersen (2008), Melvin and Taylor (2009) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a)) and the potential crash risk to these strategies (Daniel and Moskowitz (2011)). We extend this literature on strategy risk by providing direct evidence of the performance characteristics of trend following subsequent to financial crises.

In summary our paper makes three key contributions. First, we provide evidence on the long term performance of trend following using a diversified multi-country multi-asset class portfolio using data beginning in the 1920s. Second, we are the first paper to provide direct evidence on the performance of trend following during financial crises, analyzing both global and regional crises. Third, we examine the underlying markets to identify the cause of the differing performance across crisis and no-crisis periods.

The remainder of the paper is organised as follows: 1) we describe the dataset we use to create our trend following portfolios and our sample of global and regional crises; 2) we describe the methodology we use to create our trend following portfolios; 3) we provide results on the performance of trend following during global financial crises; 4) we provide results on the performance of trend following for regional financial crises; 5) we conclude with a discussion of our key findings.

Data and sample

In this section we describe how we classify our sample into crisis and no-crisis periods and the data sources used in the analysis.

Sample period

In this paper we consider both global and regional crises. As described below, we create a global portfolio to analyse the performance characteristics of trend following during global crises and a series of regional portfolios to provide additional evidence from more localised crises. Accordingly we have two samples; one to cover the global portfolio and the second to cover regional portfolios.

Identifying a list of global and regional financial crises is problematic. For simplicity we use the list of crises identified in two of the most highly cited studies of financial crises (Kindleberger and Aliber (2011) and Reinhart and Rogoff (2009)). Exhibit 1 describes the list of global financial crisis examined. These are the Great Depression in 1929, the 1973 Oil Crisis, the Third World Debt crisis of 1981, the Crash of October 1987, the bursting of the Dotcom bubble in 2000, and the Sub-Prime/Euro crisis beginning in 2007.[3] [4] The start date for each crisis is considered to be the month following the equity market high preceding the crisis.

[3] Two other additional crises were considered for inclusion in the study. Kindleberger and Aliber (2011) describe a currency crisis in the 1950s and 1960s in their list of financial crises. However, an examination of the details of this period shows it is a series of individual regional crises stretching over a decade and a half, and consequently unsuitable for inclusion in this study. A second possible candidate for inclusion is the period around 1990, with the collapse of the Japanese economy, an oil price spike and the first Iraq war. However, as it was not included in Kindleberger and Aliber (2011) or Reinhart and Rogoff (2009) as a global crisis, we do not include it in our study.

[4] We refer to crises using the start date, as defined by the equity market high.

<Insert Exhibit 1 here>

The regional crisis countries/regions (with year of inception in parenthesis) are Spain (1977); Norway (1987); Nordic (1989); Japan (1990); Mexico (1994); Asia (1997); Colombia (1997) and Argentina (2000). The list comprises crises identified by Kindleberger and Aliber (2011) and Reinhart and Rogoff (2009). All the crises except Mexico are noted by Reinhart and Rogoff (2009), while Kindleberger and Aliber (2011) do not consider Spain, Norway, Nordic, Colombia and Argentina.

<Insert Exhibit 2 here>

Futures returns

The data set for the global analysis consists of twenty one commodities, thirteen government bonds, twenty one equity indices, and currency crosses derived from nine underlying exchange rates (see Exhibit 2, column 1 for the full list) covering a sample period from January 1921 to June 2013.[5] The data consists of a combination of exchange traded futures data and forward prices derived from historical data. Appendix A provides a more detailed description of the data sources, which generally consists of DataStream/MSCI for the more recent prices (from 1980) and Global Financial Data for the older price histories.

The data for the regional crises is also sourced from DataStream/MSCI and Global Financial Data. All the return series in the regional analysis are forwards calculated from the underlying price series.[6] Exhibit 3, column 5 lists the source for each of the underlying

[5] We exclude the period from January 1940 to December 1949 from our sample due to concerns about data accuracy around World War II.
[6] Exchange futures data is available for Japan but we use a consistent methodology across all countries for the regional analysis.

instruments. Risk free rates come from Global Financial Data while yields are calculated from total return indices for both equity indices and bonds.

The analyses in this paper are based on continuous cumulative excess return series for each of the instruments. There are two methods used to create these series. 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 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 contract 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 ensure the comparability of synthetic forwards and actual exchange traded futures, 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.

Global portfolio descriptive statistics

Exhibit 2, columns 4 and 5 present summary statistics of the continuous return series used in our global sample. Typically excess returns are positive with the exception of some commodities with a negative roll yield (see Erb and Harvey (2006) and Gorton and Rouwenhorst (2006)). The different asset classes also have quite different volatilities with equity indices and commodities having much higher volatility than fixed income and currencies. Within asset classes, fixed income has the largest cross sectional differences in relative volatility with shorter term bond futures having significantly lower volatility than long term equivalents.

In Exhibit 2, columns 6 and 7, we present summary statistics for the different continuous return series during financial crisis periods, defined as the two years after the start of the crisis. Contrasting these with the full sample statistics it is noteworthy that equity returns are negative across all equity indices and countries (except Sweden and Korea), bond returns are reasonably similar, commodity returns are mostly negative and all currencies suffer depreciation versus the US dollar.

Regional descriptive statistics

<Insert Exhibit 3 here>

Exhibit 3 reports descriptive statistics for the regional crisis forward contracts. With the exception of Spain, we consider the crises start date as the prior local equity market high. As stock markets globally, including Spain, were in a bear market since the 1973 Oil Crisis, and as the crisis is listed as occurring in 1977 by Reinhart and Rogoff (2009) we use January 1977 as the start date for Spain. Within the regional crisis there is a mixture of instruments available. Equity index data is available for all crises, whereas government bond data is unavailable for Norway, Finland, Indonesia, Philippines, Colombia and Argentina. Currencies are included only for Spain, Norway, Nordic, Japan and Colombia as the other regions had currencies pegged to the dollar.

Methodology

In this section we describe the methodology used to create the trend following global and regional portfolios and to empirically test for changing behaviour in the underlying markets in crisis and no-crisis periods.

Trend following portfolios

In order to investigate the performance of trading strategies, we analyse the return series of portfolios generated from momentum signals. These portfolios are created from diversified ranges of both instruments and momentum strategies. Each momentum signal is defined in terms of its look back period, *k*, such that if the cumulative excess return over the last *k* months is positive the momentum signal is +1, and if it is negative the signal is -1. The momentum signal for time *t* is

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

Here, $M_{t,k}^{i}$ 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*.[7] In order to take a diversified measure of momentum, we use the range of values of k from 1 to 12, so the diversified momentum measure[8] for each instrument is

$$M_t^i = \frac{1}{K} . \sum_1^K M_{t,k}^i \tag{3}$$

M_t^i is the momentum of instrument *i* at time *t* and *K* is the number of different look back periods. Each instrument is given a weight proportional to the diversified momentum signal, between +/- 1, and inversely proportional to its volatility, so the size of the position is,

$$w_t^i = M_t^i . \frac{V_T}{\sigma_t^i} \tag{4}$$

The weight, w_t^i , is the holding in instrument *i* at time *t* and σ_t^i is the corresponding volatility. The position is scaled by a target volatility, V_T. The choice of this is arbitrary but it is set at 40% (consistent with Moskowitz et al. (2012)) which allows the resulting portfolio return series to have a volatility level equivalent to those reported in the literature and market indices, facilitating comparison. Each position is then held for a period of one month so that the return series for an instrument is

$$m_t^i = er_t^i . w_t^i \tag{5}$$

Here m_t^i is the excess return of instrument *i*, in time period *t*.

The final stage of the process combines the return series of the individual instruments into a single return series representing the return of a diversified momentum strategy. A two-step process is used to generate the return series. First, the average return across assets in an

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[7] Using price return rather than excess return to calculate momentum produces almost identical results.

[8] This method produces identical return series to the Moskowitz et al. (2012) methodology, although, Moskowitz et al. (2012) produce return series for each momentum strategy and then average these.

asset class is calculated and the mean return of the asset classes is calculated. This has the effect of splitting risk equally between the four asset classes and then equally between assets within each class.

The excess return and momentum series are analysed as calendar month returns. When monthly return series are created from daily series, these are calculated as calendar month returns. For the regional crises, returns are examined from the perspective of a US investor, with the currency exposure of the underlying investment assumed to be hedged and profit or loss converted to US dollars at the end of the month.[9] [10]

Ex-ante volatility

As volatility of the instruments in the universe varies from 2% to 50% (see Exhibit 2) an *ex-ante* estimate of volatility is required to scale returns to allow for comparison of results across different assets. This is necessary for both portfolio construction and regression analysis. As in Moskowitz et al. (2012), we use an exponentially weighted squared daily return model to estimate volatility. This model is similar to a univariate GARCH model. The annualised volatility for each instrument is calculated as

$$\sigma_t = \sqrt{261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \overline{r_t})^2} \qquad (6)$$

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.[11]

[9] We do not include transaction costs for the currency hedging but these are likely to have a negligible effect on returns.
[10] Our results are robust to this assumption. Analysing returns in local currency leads to almost identical conclusions on performance.
[11] In the case where only monthly data is available, δ is chosen to give a center of mass of three months.

Transaction costs and fees

In order to allow comparison with actual fund results, transaction costs and fees are included in the calculation of portfolio performance.[12]

We use the cost estimate model described by Hurst et al. (2012), outlined in Exhibit 4, defining costs as a proportion of the nominal value traded. The transaction costs are a function of asset class and time period. The costs of trading different assets within the same class are assumed to be similar. The starting point for Hurst et al. (2012) is the cost model of a large investment management firm which is used to produce cost estimates for the most recent period (2002 - 2012). Based on Jones (2002), who shows that the level of costs remained constant from 1930 to 1980 and have fallen by about 80% subsequently, Hurst et al. (2012) derive estimates for earlier periods.

<Insert Exhibit 4 here>

In general, these estimates are consistent with other literature. Significant falls in trading costs, in line with Jones (2002), are recorded by Aitken, Frino, Hill, and Jarnecic (2004), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2006) and Subrahmanyam (2007). Similarly, estimates of current futures trading costs in the literature tend to be line with these estimates (see for example Locke and Venkatesh (1997), Burnside et al. (2006) and Szakmary, Shen, and Sharma (2010)).

Management and incentive fees are applied where indicated. These are set at typical values (Hurst et al. (2012)) of 2% and 20% respectively. Incentive fees are calculated monthly and include a high watermark.

[12] Transaction costs are included in all the results shown. Management fees are only included where specified.

Time series behaviour of markets

In order to examine why trend following performance might vary across different time periods it is necessary to identify differences in the time series characteristics of the underlying futures markets between these periods.

Moskowitz et al. (2012) provide evidence on the time series predictability of futures markets, from 1965 to 2009, using regression analysis. Taking a similar approach to examine predictability, for each futures contract, i, we regress the excess return, er_t^i, on its lagged excess return, er_{t-l}^i. The univariate regressions are carried out with a lag, l, where l ranges from 1 to 24 months. All the observations for each lag are stacked to allow a pooled panel regression. Given the wide range of volatilities in the universe, observations are normalised using the lagged *ex-ante* volatility, σ_{t-1}^i. The regression equation then becomes:

$$er_t^i/\sigma_{t-1}^i = \alpha + \beta_1 er_{t-l}^i/\sigma_{t-l-1}^i + \varepsilon_t^i \qquad (7)$$

In comparing the regressions from crisis and no-crisis periods we focus on reporting the regression βs as, unlike the t statistics, the βs are insensitive to changes in sample size. Due to limited data size we are unable to draw statistically significant conclusions on the differences between individual βs in the crisis and no-crisis periods, however we are able to test for statistically significant differences in the cumulative βs.

In the following section we present a number of analyses comparing market characteristics in crisis and no-crisis periods. Unfortunately, Kindleberger and Aliber (2011) and Reinhart and Rogoff (2009) do not provide guidance on the length or end date of each crisis. Rather than attempting to define when each individual crisis ends, instead we focus our analyses on two fixed time periods, twenty four months and forty eight months, post the prior equity market high as our "crisis periods". Data outside of these time intervals is considered "no-crisis periods". While we acknowledge that our sample of crises is heterogeneous and do not last for a fixed period of time, it is a reasonable assumption that the majority of the data within these fixed time intervals can be considered crisis period data, and so an analysis of that data will produce results representative of a market crisis.

Results

We begin by focusing on the performance of the global portfolio and the time series behaviour of futures returns during financial crises before moving on to provide some evidence from the regional crisis periods.

Global financial crisis portfolio performance

<Insert Exhibit 5 here>

<Insert Exhibit 6 here>

Before examining the performance of the trend following portfolio in crisis periods first we review the performance of the portfolio across the full sample period. Exhibit 5 graphs the cumulative returns for the global portfolio from 1925 to 2013.[13] The average return net of fees is 12.1% with volatility of 11%. To ensure that the portfolio is capturing the characteristics of trend following CTAs we plot the returns of the portfolio against the returns of the Newedge Index of Trend Following CTAs over the period 2000 to 2013 (Exhibit 6). The two series are highly correlated with a coefficient of 0.76.

<Insert Exhibit 7 here>

Looking at performance in crisis and no-crisis periods, Exhibit 7, Panel A, displays results for the full sample period from 1925 to 2013. Performance is reported for the global

[13] Including pre-1925 returns leads to larger performance differences between Crisis and No-Crisis periods. However we exclude these portfolio returns as they are formed using volatility estimates generated using relatively short time series of asset returns.

portfolio (net and gross of fees) and by asset class. This information is displayed graphically in Exhibit 8.

<Insert Exhibit 8 here>

Column two reports the performance for each portfolio over the full period. The Sharpe ratio for the global portfolio is an impressive 1.1. Looking at individual asset classes the performance of Equity Indices and Government Bonds is better than the other two, Currencies and Commodities.

The performance comparison for the twenty four month crisis period is reported in columns three to five. Column three reports crisis period performance, column four reports performance excluding the crisis period, and column five reports the difference between column four and three. Columns six to eight report the same results, this time for a crisis period defined as lasting forty eight months.

The results are very consistent. Comparing the performance of the first two years of trend following subsequent to a crisis the returns are far lower than in the no-crisis sample. At the full portfolio level the average return in the first twenty four months of a crisis is 4%, versus 13.6% in the no-crisis months. The return in the four year period from the start of a crisis averages 6%, versus 14.9% in the no-crisis sample. Across asset classes, the results for Equity Indices, Government Bonds, and Currencies are all consistent, with a difference in Sharpe ratio ranging from 0.19 to 0.71. Only Commodities generate returns of a similar magnitude in crisis and no-crisis periods. The results for commodities are consistent with prior evidence on the lack of synchrony between the cycle of commodities and other asset classes (see for example Erb and Harvey (2006) and Gorton and Rouwenhorst (2006)).

As a robustness check we repeat the analysis focusing on the period from 1980 to 2013, where exchange traded futures data is available. These results are reported in Exhibit 7 Panel B. The results are remarkably consistent with Panel A. For a two year crisis period the full portfolio net of fees generates returns almost one third of those earned in no-crisis periods. The only exception is Currencies where four years into the crisis the performance differential is zero for the crisis and no-crisis returns.

Global financial crisis time series effects

Next, we examine the predictability of these markets to establish whether there is a difference in the time series behaviour of futures markets between crisis and no-crisis periods.

<Insert Exhibit 9 here>

Exhibit 9 reports results of these tests for the full sample. Consistent with Moskowitz et al. (2012), there is strong return continuation for the first twelve months, with limited evidence of subsequent reversals. When we next divide the sample into crisis and no-crisis periods, the different dynamics become very apparent. Within crisis periods the return continuation disappears. Reversals occur in months five, six and eight and the beta of continuation months is smaller. With significantly weaker relationship between return months the opportunities for profitable trend following are diminished. Excluding crisis periods, the pattern of strong continuations becomes very evident. Unlike crisis periods, the no-crisis periods provide plenty of profitable opportunities for trend followers.[14]

[14] Repeating the analysis with longer duration crisis period definitions provides very similar results.

<Insert Exhibit 10 here>

To examine time series characteristics of the different asset classes we repeat the analysis for each. Exhibit 10 reports betas for crisis and no-crisis periods by asset class. Equity Indices, Government Bonds and Currencies have strong return continuation out to twelve months in no-crisis periods, whereas there are reversals in at least two of the first six months evident in the crisis periods. The only exception is commodities, which have strong return continuations for the first five months into the crisis, before reversing. This explains why the crisis returns are higher than no crisis returns for commodities, as seen in Exhibit 7.

<Insert Exhibit 11 here>

An alternative view of the regressions is presented in Exhibit 11. Here, the cumulative sum of the regression coefficients (Betas) is shown, along with it 95% confidence interval, for crisis and no-crisis periods. This is shown for the full universe of assets and also by asset class. The degradation in autocorrelation as markets move to crisis periods is evident. After twelve months, the cumulative beta of for the no-crisis period is significantly (95% confidence level) above the crisis period for the full portfolio, equity indices and currencies, while the difference for government bonds is also evident but falls short of statistical significance. The commodity market is, as expected, the exception, with similar crisis and no-crisis results.

Regional financial crises performance

Given there are only six global crisis we also provide additional evidence using a range of regional crises. Summary results for the regional crises are reported in Exhibit 12. Panel A displays the cumulative returns of an equally weighted portfolio made up of the eight individual financial crisis portfolios, all aligned with the prior equity market high at month 0. Performance is relatively weak for the first two to three years into the crisis.

<Insert Exhibit 12 here>

Looking next at the summary performance statistics of the individual crisis reported in Panel B, it is evident that there is significant cross-sectional deviation across crises performance. For example in year 1, when the average return across crises is -1.3%, the range of crisis returns is from -14.7% to +11.5% Again in year 2 the average crises return is 2.9% with a range of outcomes, from -8.4% to 8.1%. In years 4 to 6 average returns gradually increase up to 9%, but in each year the range remains wide, and at least one of the crisis portfolios generates negative returns.

A comparison of crises

The heterogeneous nature of the global crises makes it difficult to compare individual crises. There are however a number of features that can be highlighted. Exhibit 13 Panel A graphs the cumulative returns for the trend following portfolio for each crisis period. The crises can be loosely classified into two groups, those that develop quite rapidly (1929, 1987 and 2000) and those that develop more gradually (1973, 1981 and 2007). The first group tend to start with a period of very poor trend following performance, generally due to losses in the equity index sub-portfolio, as the equity indices reverse quite sharply. The crises which develop more slowly allow time for the trend following signals to adjust to the new market direction before the crisis fully develops, resulting in short run profitability.

<Insert Exhibit 13 here>

The poor performance during market crises is generally due to extended periods where cumulative returns move sideways rather than experiencing significant drawdowns.

These periods are characteristic of all the crises we have examined. The longest period each crisis undergoes without generating an excess return (net of cash) is presented in Exhibit 13, Panel B. This ranges from 18 months (2000) to 54 months (1987) and averages three years. It is notable that this extended period of weak performance begins at different intervals in the crises.

It is only possible to comment on regional crises at an aggregate level due to the scale of heterogeneity in the individual results. The general pattern, a period of poor performance followed by an improvement in performance is consistent with the return series of the global portfolios. Here the aggregate excess returns are close to zero in the first two years, with performance beginning to improve through years three and four.

Taken together the results reported in this section of the paper provide clear evidence on the effect of financial crises both on trend following performance and the underlying markets traded by these funds. The performance of these types of strategies is much weaker in crisis periods, where performance can be as little as one third of that in normal market conditions. This result is supported by our evidence for regional crises, though the effect seems to be more short lived. In our analysis of the underlying markets, our empirical evidence indicates a breakdown in the time series predictability, pervasive in normal market conditions, on which trend following relies.

Conclusions

In conclusion, this paper has taken an extensive look at the long term performance of trend following strategies, how those strategies perform during regional and global financial crises periods and what happens to the underlying markets traded by funds pursuing these strategies.

Our analysis of the long term performance of trend following strategies using a diversified global multiple asset class portfolio from 1925 to 2013, suggests that these strategies have produced consistently high returns through time. Despite the below average recent performance of trend following funds, this should give investors in funds employing these types of strategies some comfort.

Looking next at the performance of these strategies during financial crises the evidence is consistent. These strategies typically underperform for an extended period, on average four years, following a crisis. Performance outside these crisis periods is more than double the crisis returns.

Repeating the analysis focusing on regional crises, the results are consistent with the global performance. Although individual crises differ significantly, the pattern of a period of poor performance followed by reversion to long term norms is repeated, although here performance begins to pick up during the third year after the crisis.

We find significant differences in the time series dynamics of the underlying markets between crisis and no-crisis periods. In futures markets there are strong autocorrelations in time series returns of instrument at lags of one to twelve months, which drive trend following returns. By dividing the data between crisis and no-crisis periods, we find that during periods of financial crisis, this relationship is significantly diminished. This has the consequence of significantly reducing the returns of the trend following strategy.

Our research leads to a key question which remains unanswered - What happens to cause this break down in the time series behaviour of futures markets following a financial crisis?

Existing behavioural finance theories provide some predictions which our results support. For example Daniel et al. (1998) and Hong and Stein (1999) link serial correlation in asset returns to increases in overconfidence and decreased risk aversion of investors. Precisely the opposite conditions occur in a financial crisis with investor confidence falling and increasing risk aversion. Under both models, opportunities for generating trend following returns should decrease in these periods.

Also as noted by Daniel, Hirshleifer, and Teoh (2002), governments have an increased tendency to intervene in financial markets during crises, resulting in discontinuities in price patterns. The Federal Reserve's support of Bear Sterns in March 2008 (Melvin and Taylor (2009)) and the intervention by the Hong Kong Monetary Authority in Hang Seng futures in 1998 (Bhanot and Kadapakkam (2006)) both caused sharp reversals in their respective markets. The frequency, effect and consequences of these interventions for trend following requires further research.

Finally, hedging pressure has long been recognised as having a role in the price setting mechanism of commodity markets. De Roon, Nijman, and Veld (2000) demonstrates that hedging pressure has a significant effect on the futures risk premia, so changing dynamics in hedging pressure during crisis may cause changes in market characteristics. More explicitly, Moskowitz *et al.* (2012) link the returns of trend following with the cost of hedging, as speculators (trend-followers) capture a premium from hedgers. It is possible that, as hedgers benefit from positions in a crisis, the premia normally paid by hedgers to speculators is reversed.

It should be stressed that while the above points suggest mechanisms by which market states may differ from crisis to no-crisis periods, we do not present evidence that these changes occur, or if they do, that they are the cause of the time series effects that we have identified in our analysis. Significant further research is needed to fully understand their effects on the markets and on the return characteristics of time series momentum.

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 from 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 (SPI 200), 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 (IBEX 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. The data for eight of these is extended backwards using total return indices and short term yields from Global Financial Data. As the Australian bond futures are quoted as (100 – interest rate), these returns were normalised to facilitate the combination of synthetic and market price series.

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 sourced 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 Australian Dollar, Canadian Dollar, Euro (German Mark), Norwegian Krone, New Zealand Dollar, Swedish Krona, Swiss Franc, United Kingdom Pound and United States Dollar.

A.4 Commodities

Twenty one commodities are traded, 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, provided by Datastream. As cost of carry data is unavailable it is not possible to accurately estimate forward prices prior to the availability of exchange traded futures.

A.5 Risk free rates

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

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Exhibit 1

Global Financial Crises: Data Set

Crisis	Start Date	Data Source
Great Depression	Oct-1929	GFD
Oil Crisis	Oct-1973	GFD
Third World Debt	Aug-1981	Exchange/MSCI/GFD
Black Monday	Oct-1987	Exchange/MSCI
Dotcom Bubble	Mar-2000	Exchange
Sub Prime/Euro	Jul-2007	Exchange

Exchange: Exchange Traded Futures Contract. MSCI: Forward derived from MSCI data. GFD: Forward derived from Global Financial Data.

Exhibit 2: Descriptive Statistics

			Full Sample		Crisis Period	
	Start Date Derived	**Start Date Exchange**	**Annualized Mean Return (%)**	**Annualized Volatility (%)**	**Annualized Mean Return (%)**	**Annualized Volatility (%)**
Commodity Futures						
COCOA		Jan-80	-8.14	29.67	-1.42	35.60
COFFEE		Jan-80	-6.80	37.53	-11.88	35.71
COPPER		Oct-88	5.82	26.21	-8.94	30.90
CORN		Jan-80	-5.13	25.32	-12.99	30.03
COTTON		Jan-80	-3.62	26.36	-17.36	27.24
GAS OIL		Sep-03	13.39	30.88	-8.20	44.36
GOLD		Jan-80	3.25	17.98	0.45	20.96
LEAN HOGS		Jan-80	-2.93	25.10	-17.13	23.37
LIGHT CRUDE OIL		Mar-83	6.42	34.72	2.30	39.35
LIVE CATTLE		Jan-80	1.71	14.30	-0.81	14.71
NATURAL GAS		Apr-90	-12.09	58.26	-30.25	73.89
NY HEATING OIL		Jan-80	6.55	32.66	2.77	32.76
PALLADIUM		Jan-80	7.95	33.38	0.77	46.71
PLATINUM		Jan-80	0.04	25.04	-5.88	32.03
RBOB GASOLINE		Oct-05	7.60	34.77	-14.85	49.34
SILVER		Jan-80	-5.66	31.48	-9.53	30.87
SOYABEAN MEAL		Jan-80	4.23	26.33	10.91	29.72
SOYABEAN OIL		Jan-80	-2.91	26.27	-13.02	29.96
SOYABEANS		Jan-80	-0.47	23.64	-3.97	27.69
SUGAR		Jan-80	-5.87	39.34	5.01	45.11
WHEAT		Jan-80	-7.66	25.14	-13.18	26.78
Bond Futures						
Australia -10Y	Jan-21	Jun-85	0.44	6.83	-1.70	10.03
Australia - 3Y		May-88	4.34	9.81	-0.53	9.61
Canada - 10Y	Jan-50	Sep-89	1.22	6.26	3.57	9.49
US - 5Y	Jan-21	May-88	0.89	4.54	3.48	5.88
US - 2Y		Jun-90	1.72	1.74	3.85	1.97
US - 10Y	Jan-21	May-82	1.21	6.10	3.99	7.95
US - 30Y	Jan-21	Jan-80	1.12	9.13	3.88	11.64
Germany - 5Y		Oct-91	3.01	3.25	2.47	3.73
Germany - 30Y		Sep-05	5.28	12.48	4.30	10.97
Germany - 2Y		Mar-97	0.99	1.38	1.00	1.82
Germany - 10Y	Jan-50	Nov-90	2.18	5.08	3.87	5.63
Japan - 10Y	Jan-21	Dec-86	1.99	5.09	1.62	5.92
UK - 10Y	Jan-21	Nov-82	0.07	7.84	3.40	10.39
Equity Index Futures						
SPI 200 - Australia	Feb-21	May-00	4.38	15.89	-15.85	26.12
S&P TSX 60 - Canada	Jan-70	Nov-11	2.72	16.60	-10.70	21.93
Dow Jones - US		Oct-97	7.30	17.10	-11.03	23.64
NASDAQ 100 - US		Apr-96	6.28	28.50	-31.60	37.87
AEX - Netherlands	Jan-70	Jun-88	4.71	19.11	-8.80	23.46
CAC 40 - France	Jan-70	Jun-92	2.91	20.46	-9.38	24.01
DAX - Germany	Jan-50	Apr-96	5.64	18.63	-8.66	22.48
MDAX - Germany		Mar-05	9.29	22.99	-29.06	33.09
HANG SENG - Hong Kong	Jan-70	Apr-97	10.70	33.67	-23.31	39.25
S&P Midcap - US		Feb-92	2.37	15.76	-13.65	18.01
NIKKEI 225 - Japan	Jan-50	Mar-99	6.01	20.39	-14.03	20.62
S&P 500 - US	Jan-21	Oct-90	4.89	19.12	-14.52	22.61
KOSPI 200 - Korea	Jan-65	Mar-05	9.04	27.69	2.56	27.97
FTSE 100 - UK	Feb-21	Oct-88	4.28	16.80	-10.14	27.57
IBEX 35 - Spain	Jan-70	Oct-97	0.80	21.02	-13.14	21.02
MIB - Italy	Oct-50	Nov-90	1.46	22.06	-23.00	23.72
Russell 2000 - US		Apr-07	2.23	23.93	-20.31	28.49
OMXS 30 - Sweden	Jan-70	Feb-92	6.43	22.19	1.70	25.90
SMI - Switzerland	Jan-70	Sep-99	5.11	16.64	-7.38	19.07
SMI Midcap - Switzerland		Sep-05	2.13	19.00	-27.11	26.40

Exhibit 2: Descriptive Statistics Continued

Currency Forwards					
AUD/USD	Jan-73	-1.54	11.72	2.36	14.66
CAD/USD	Jan-73	-0.51	6.63	0.90	8.21
CHF/USD	Jan-73	-0.66	12.55	2.14	12.98
EUR/USD (DEM/USD)	Jan-73	0.28	11.20	5.78	12.13
GBP/USD	Jan-73	-0.69	10.34	6.56	10.94
JPY/USD	Jan-73	-0.02	11.42	5.90	12.49
NOK/USD	Jan-73	-1.38	10.79	3.66	10.79
NZD/USD	Jan-73	-1.80	12.64	6.94	15.95
SEK/USD	Jan-73	0.10	11.31	8.35	12.65

The table summarizes the key attributes of the instruments used in the study. Two start dates are included, the first is the start date for derived forward contracts and the second is the start date for exchange traded future contracts. The performance of the instrument is summarized by two measures; mean annual return and annual volatility. This is shown first for the full sample and then for the two year period after the start of a financial crisis. Currencies are quoted as local units per USD.

Exhibit 3

Regional Crises: Summary Statistics

Region	Start	Country	Instrument	Data Source	Full Sample Mean	Full Sample Vol.	Crisis Periods Mean	Crisis Periods Vol.
Spain	Jan-77	Spain	Equity	D/M	4.12	39.48	5.95	67.71
			Bond	GFD	-12.67	16.92	-6.71	19.17
			Currency	GFD	-5.01	9.77	-2.98	12.89
Norway	Oct-87	Norway	Equity	D/M	4.84	12.05	-2.81	18.16
			Currency	D/M	-2.35	26.80	-0.48	33.46
Nordic	May-89	Sweden	Equity	D/M	-4.67	10.62	-0.65	9.62
			Bond	D/M	3.72	25.28	-2.63	28.09
			Currency	D/M	0.32	10.07	-0.14	10.19
		Finland	Equity	D/M	-1.35	12.64	-1.51	8.88
			Currency	D/M	-3.35	28.07	-9.16	24.90
Japan	Feb-90	Japan	Equity	D/M	-2.86	13.28	-1.77	10.36
			Bond	D/M	-7.83	23.33	-7.77	29.46
			Currency	D/M	2.34	7.43	-0.01	8.34
Mexico	Mar-94	Mexico	Equity	D/M	-1.27	11.59	-1.86	10.89
			Bond	GFD	-2.61	28.25	-2.94	31.69
Asia	Mar-97	Hong Kong	Equity	D/M	-2.48	22.03	6.14	37.34
			Bond	GFD	-6.49	31.09	-3.21	47.19
		Indonesia	Equity	D/M	3.63	7.72	-0.09	13.01
		Korea	Equity	GFD	-16.63	44.73	-8.18	68.91
			Bond	GFD	-2.24	44.36	3.76	64.69
		Malaysia	Equity	D/M	4.59	8.42	1.88	13.31
			Bond	GFD	-7.67	37.77	-4.80	61.74
		Philippines	Equity	D/M	4.04	5.82	0.14	6.84
		Thailand	Equity	D/M	-21.28	32.27	-5.41	45.03
			Bond	GFD	-15.88	50.70	-2.31	77.16
Colombia	Dec-97	Colombia	Equity	D/M	9.83	17.52	3.32	27.55
			Currency	GFD	1.06	34.41	-11.44	44.29
Argentina	Apr-00	Argentina	Equity	D/M	3.91	9.29	0.47	10.54

The table lists the key features of the data sample used in analysing regional crises. The crises are listed with start date and countries involved. The instruments used and their data source are then listed, with GFD representing Global Financial Data and D/M being MSCI via DataStream. The final columns summarize the performance of these instruments in terms of annual return and annual volatility. The full sample period is an eight year span starting one year before the crisis. The crisis period represents a two year period from the crisis start date. Short term interest rates sourced from GFD. Currencies are quoted as local units per USD.

Exhibit 4

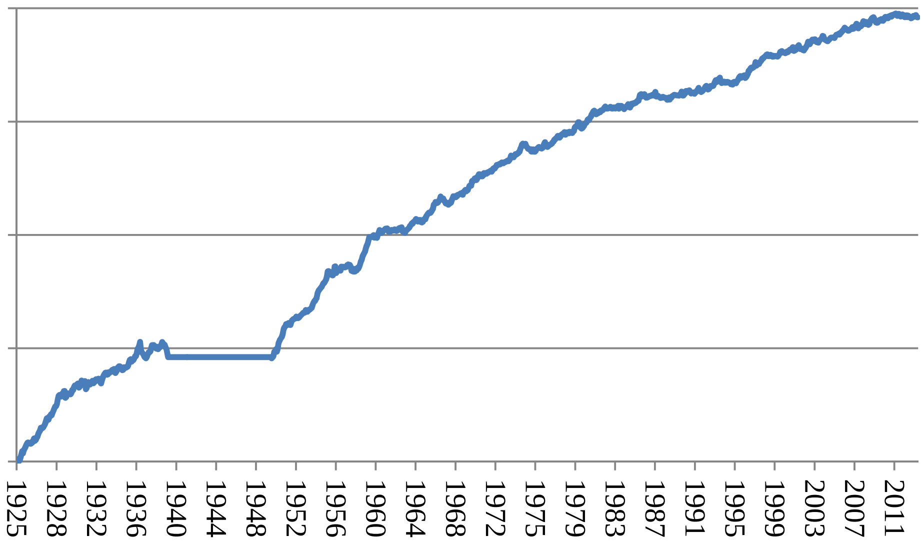
One-way Transaction Costs as a Percentage of Notional Traded, by Asset Class

	1920-1992	1993-2002	2003-2013
Equities	0.36%	0.12%	0.06%
Bonds	0.06%	0.02%	0.01%
Commodities	0.60%	0.20%	0.10%
Currencies	0.18%	0.06%	0.03%

Adapted from Hurst et al. (2012)

Exhibit 5

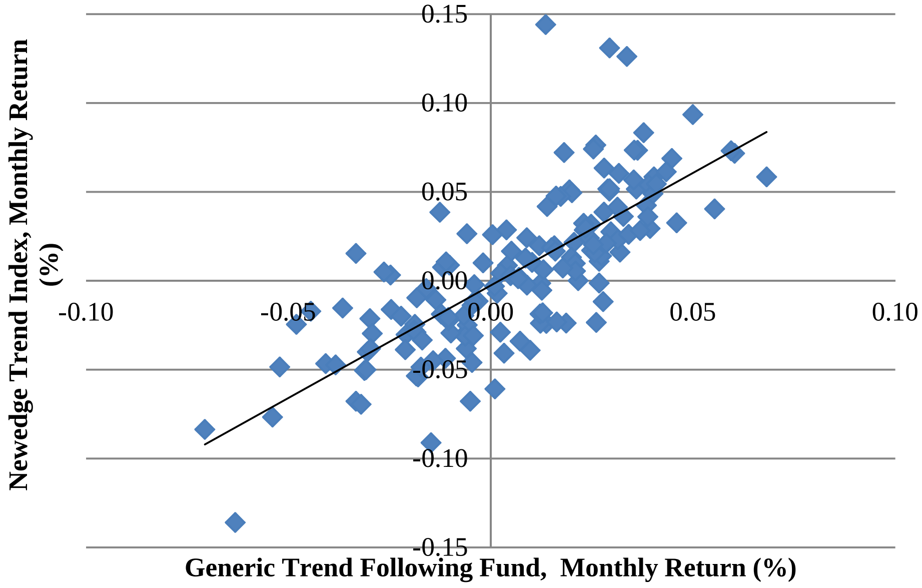
Log Cumulative Return of Trend Following Portfolio (January 1925 to June 2013)



The chart shows the log cumulative return of a diversified trend following portfolio from 1925 to 2013. The results are shown net of transaction costs and fees (2% management fee and 20% performance fee). The decade around World War II, from January 1940 to December 1949 is omitted from the analysis due to concerns about data accuracy.

Exhibit 6

Comparison of Generic Trend Following Performance with Newedge Trend Index, (January 2000 to June 2013)



The monthly performance of the generic trend following portfolio generated in the research is plotted against the corresponding Newedge trend following index performance. Generic Portfolio returns are net of trading costs, management fee (2%) and incentive fee (20%) and include a cash return.

Exhibit 7

The Performance of Trend Following during Financial Crises

Panel A: Full Sample (January 1925 to June 2013)

		Two Years			Four Years		
	All	**Crisis**	**No-crisis**	**Diff.**	**Crisis**	**No-crisis**	**Diff.**
FULL: Fees							
Return (%)	12.14	4.04	13.63	9.59	5.97	14.90	8.93
Volatility (%)	11.04	11.16	10.98	-0.18	10.92	11.03	0.11
Sharpe Ratio	1.10	0.36	1.24	0.88	0.55	1.35	0.80
FULL							
Return (%)	18.49	8.77	20.29	11.52	10.59	22.06	11.47
Volatility (%)	12.35	12.19	12.33	0.14	11.79	12.49	0.70
Sharpe Ratio	1.50	0.72	1.65	0.93	0.90	1.77	0.87
EQUITY							
Return (%)	5.13	3.47	5.44	1.97	3.68	5.76	2.08
Volatility (%)	4.78	4.91	4.75	-0.16	4.86	4.73	-0.13
Sharpe Ratio	1.07	0.71	1.14	0.43	0.76	1.22	0.46
BOND							
Return (%)	5.15	1.65	5.75	4.10	2.46	6.30	3.84
Volatility (%)	5.27	5.12	5.28	0.16	5.13	5.30	0.17
Sharpe Ratio	0.98	0.32	1.09	0.77	0.48	1.19	0.71
CURRENCY							
Return (%)	1.28	-0.02	1.71	1.73	0.99	1.60	0.61
Volatility (%)	3.28	3.57	3.17	-0.4	3.30	3.26	-0.04
Sharpe Ratio	0.39	-0.01	0.54	0.55	0.30	0.49	0.19
COMMODITY							
Return (%)	1.68	3.15	1.20	-1.95	2.74	0.60	-2.14
Volatility (%)	2.86	3.65	2.54	-1.11	3.27	2.36	-0.91
Sharpe Ratio	0.59	0.86	0.47	-0.39	0.84	0.26	-0.58

The table shows the performance of trend following strategies, at a diversified portfolio level and asset class level, from 1925-2013. All returns include trading costs. The performance is represented by the average excess return, volatility and Sharpe ratio. The first column represents the full sample period. Columns 2 & 3 break the performance into crisis and no-crisis periods assuming that a crisis lasts two years from the start date. Column 4 highlights the difference between the two. Columns 5-7 repeat the analysis in columns 2-4, but assume a crisis lasts four years.

Exhibit 7 cont'd

Panel B: Recent Sample (January 1980 to June 2013)

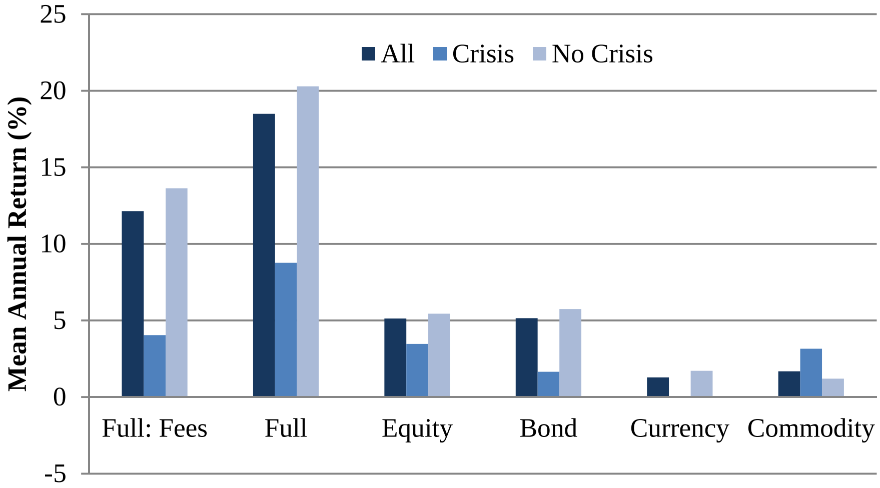
	All	Two Years Crisis	Two Years No-crisis	Two Years Diff.	Four Years Crisis	Four Years No-crisis	Four Years Diff.
FULL: Fees							
Return (%)	6.54	2.62	7.84	5.22	4.91	8.04	3.13
Volatility (%)	9.25	9.97	8.99	-0.98	9.45	9.06	-0.39
Sharpe Ratio	0.71	0.26	0.87	0.61	0.52	0.89	0.37
FULL							
Return (%)	11.22	6.73	12.71	5.98	9.21	13.08	3.87
Volatility (%)	10.12	10.74	9.90	-0.84	10.25	10.01	-0.24
Sharpe Ratio	1.11	0.63	1.28	0.65	0.90	1.31	0.41
EQUITY							
Return (%)	4.34	2.74	4.90	2.16	3.07	5.52	2.45
Volatility (%)	4.68	4.30	4.78	0.48	4.51	4.81	0.30
Sharpe Ratio	0.93	0.64	1.02	0.38	0.68	1.15	0.47
BOND							
Return (%)	3.81	0.69	4.79	4.10	2.12	5.37	3.25
Volatility (%)	5.53	5.23	5.60	0.37	5.23	5.77	0.54
Sharpe Ratio	0.69	0.13	0.86	0.73	0.41	0.93	0.52
CURRENCY							
Return (%)	1.18	0.26	1.45	1.19	1.20	1.17	-0.03
Volatility (%)	3.2	3.40	3.13	-0.27	3.28	3.13	-0.15
Sharpe Ratio	0.37	0.08	0.46	0.38	0.37	0.37	0.00
COMMODITY							
Return (%)	1.68	3.15	1.20	-1.95	2.74	0.60	-2.14
Volatility (%)	2.86	3.65	2.54	-1.11	3.27	2.36	-0.91
Sharpe Ratio	0.59	0.86	0.47	-0.39	0.84	0.26	-0.58

The table shows the performance of trend following strategies, at a diversified portfolio level and asset class level, from 1980-2013. All returns include trading costs. The performance is represented by the average excess return, volatility and Sharpe ratio. The first column represents the full sample period. Columns 2 & 3 break the performance into crisis and no-crisis periods assuming that a crisis lasts two years from the start date. Column 4 highlights the difference between the two. Columns 5-7 repeat the analysis in columns 2-4, but assume a crisis lasts four years.

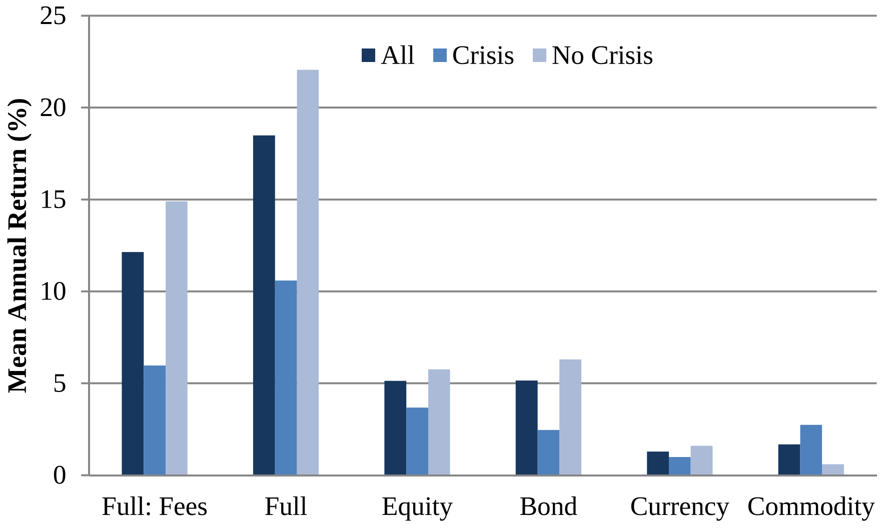
Exhibit 8

The Performance of trend following during financial crises (January 1925 to June 2013)

Panel A: Crisis Period Twenty Four Months

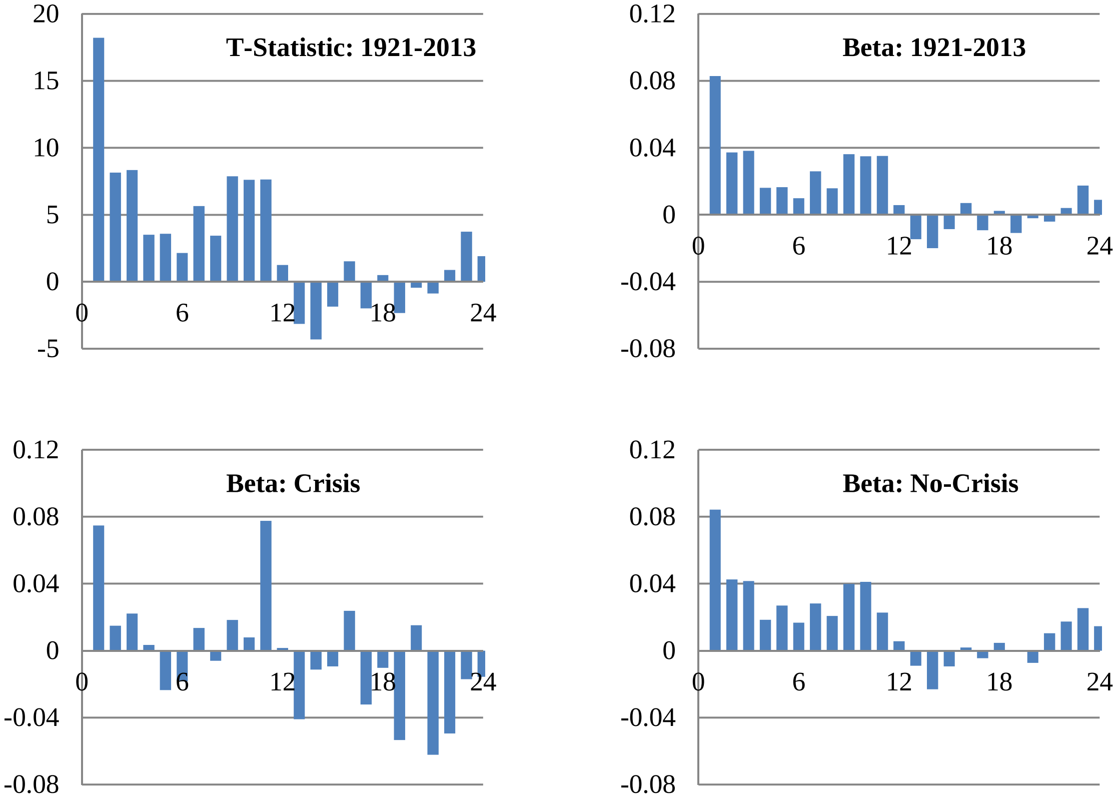


Panel B: Crisis Period Forty Eight Months



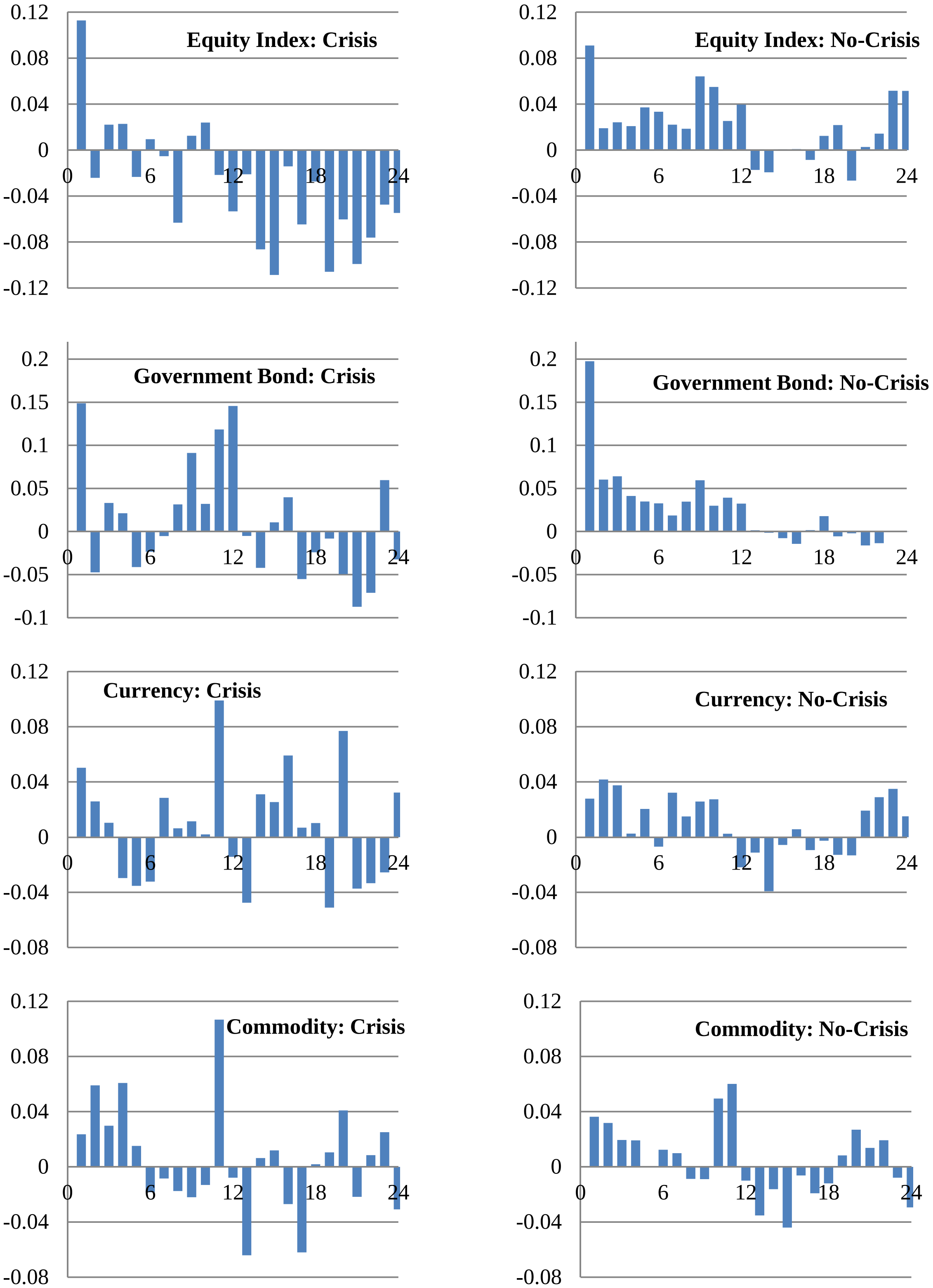
The chart shows the average annual performance of trend following strategies, at a diversified portfolio level and asset class level, from 1925-2013. All returns include trading costs. Panel A assumes a twenty four month crisis whereas Panel B assumes a forty eight month crisis period.

Exhibit 9: The Time Series Correlation of Asset Prices, All Classes



Monthly excess returns of each instrument are regressed on lagged excess returns over a range of time horizons. The sample consists of data from 1921 to 2013 and the regression model is $er_t^i/\sigma_{t-1}^i = \alpha + \beta_1 er_{t-l}^i/\sigma_{t-l-1}^i + \varepsilon_t^i$. The top two graphs report the t-statistic and β_1 for lags from one month to twenty four months. The sample is then split between crisis and no-crisis periods. Crisis periods are assumed to last two years from the start date.

Exhibit 10: The Time Series Correlation by Asset Class: Regression Beta

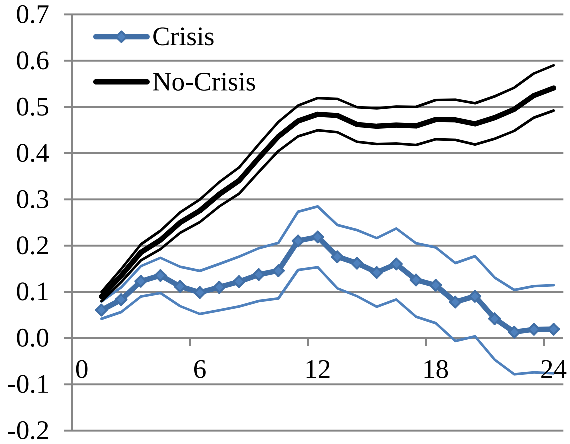


Monthly excess returns of each instrument are regressed on lagged excess returns over a range of time horizons. The sample consists of data from 1921 to 2013 and the regression model is $er^i_t/\sigma^i_{t-1} = \alpha + \beta_1 er^i_{t-l}/\sigma^i_{t-l-1} + \varepsilon^i_t$. The sample is divided by asset class and then between crisis and no-crisis periods where crises periods are assumed to last two years from the start date. The β_1 for each lag from one month to twenty four months is reported for each asset class for crisis and no-crisis periods.

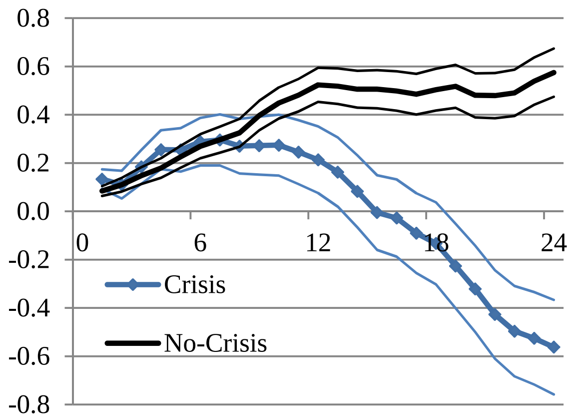
Exhibit 11

Time Series Correlation: Cumulative Beta with Confidence Interval

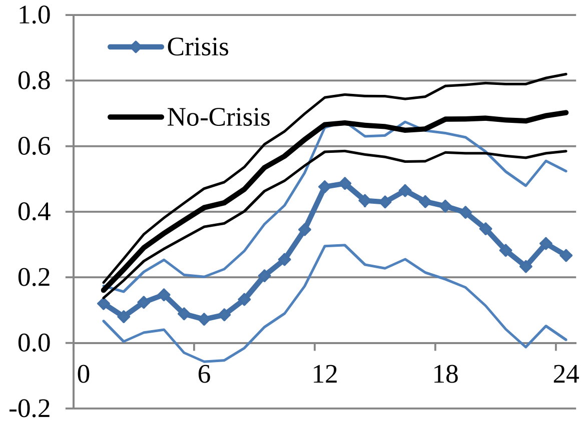
All Assets



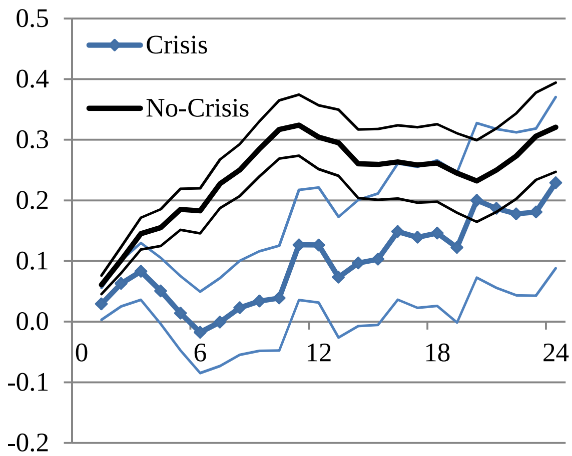
Equity



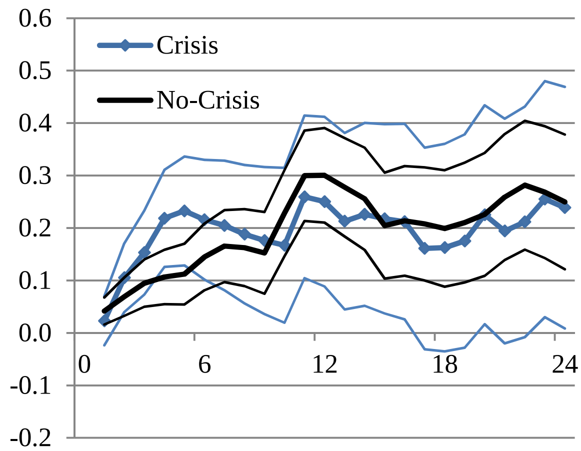
Bonds



Currency



Commodity

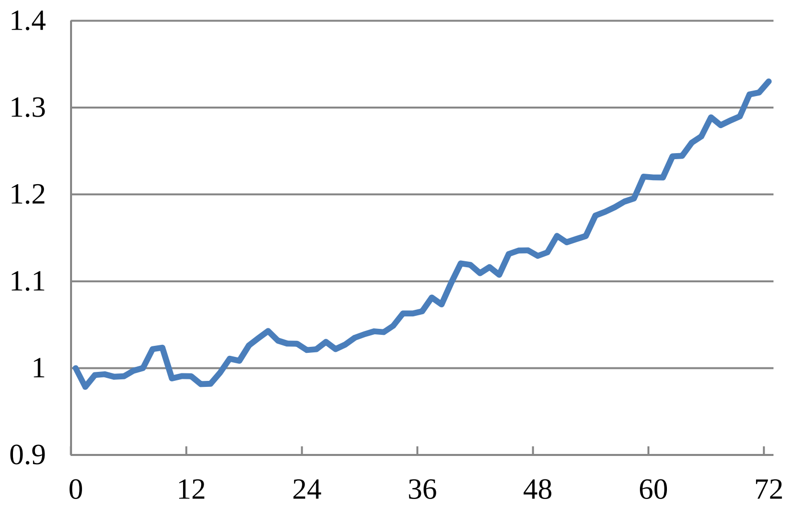


The cumulative regression coefficients from a series of lagged regressions, along with their 95% confidence interval are plotted. Monthly excess returns are regressed on lagged excess over a range of time horizons. The sample consists of data from 1921 to 2013 and the regression model is $er_t^i/\sigma_{t-1}^i = \alpha + \beta_1 er_{t-l}^i/\sigma_{t-l-1}^i + \varepsilon_t^i$. Each graph splits the sample between crisis and no-crisis periods. A crisis period is assumed to last two years from the start date.

Exhibit 12

Performance of a Trend Following Portfolio following a regional financial crisis.

Panel A: Cumulative Returns



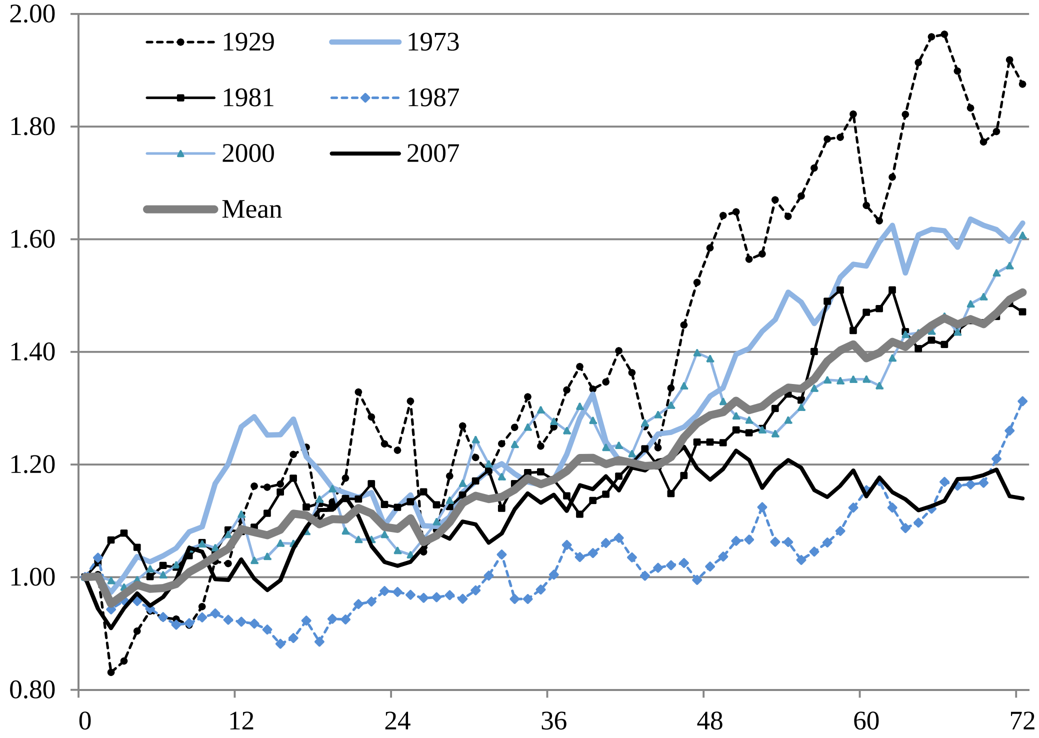
Panel B: Summary Performance Statistics

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6
Average Return (%)	-1.25	2.87	4.41	6.03	7.89	9.07
Best (%)	11.48	8.10	17.02	27.24	17.77	22.81
Worst (%)	-14.71	-8.39	-3.48	-6.94	-2.45	-5.23
Average Volatility (%)	11.80	7.60	4.75	8.84	8.13	7.02
Highest (%)	17.81	17.45	8.15	14.43	15.11	11.74
Lowest (%)	5.02	3.01	3.19	4.19	4.35	2.69

The chart shows the mean combined performance of the eight regional crises, each of which are aligned on the local stock market high. The table summarizes the performance by year. For each year, the mean return and mean volatility of the eight crises are shown. These are accompanied by the best and worst individual performance and the highest and lowest individual volatility.

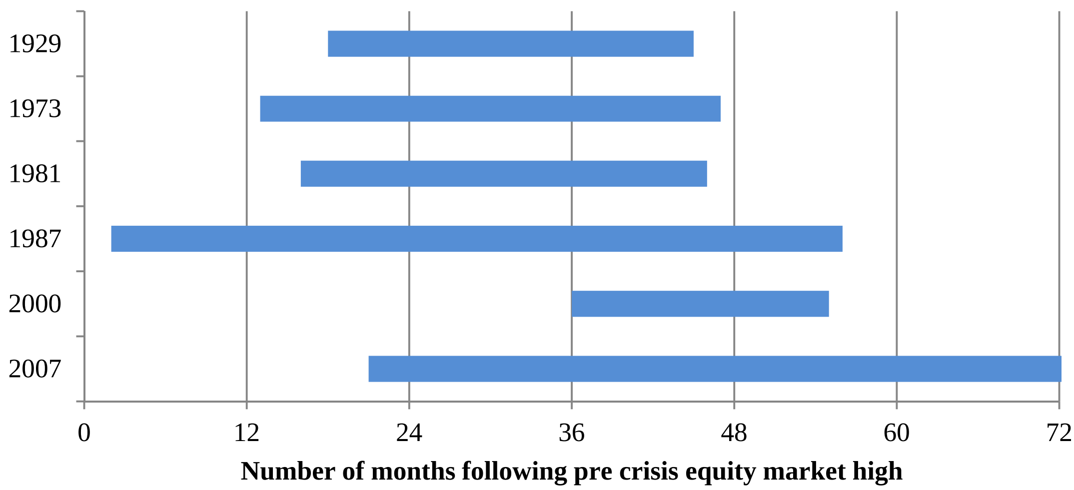
Exhibit 13

Panel A: Cumulative Returns of Trend Following Portfolio Following Global Financial Crises



Panel B

Global Crises: Maximum Period with Zero Cumulative Excess Returns



Panel A shows the cumulative return of each global crisis and the mean combined performance of the six global crises, each of which is aligned on the pre-crisis stock market high. Panel B displays the length of the maximum period that the trend following portfolio generates zero cumulative excess returns for each crisis.