Regime Change and Convertible Arbitrage Risk

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Abstract

This paper analyses the data generating process of the convertible arbitrage hedge fund strategy. Within a nonlinear framework, we allow for alternate regimes of convertible arbitrage risk using smooth transition autoregressive (STAR) models. In one regime the convertible arbitrage strategy exhibits relatively large exposure to default and term structure risk factors and negative alpha. In the alternate regime the strategy exhibits relatively low exposure to market risk factors and positive alpha. Significantly, over the sample period the strategy generally exists in the low risk/high alpha regime. We suggest that evidence reported in this paper accounts for abnormal returns reported for the strategy in previous studies.

Keywords: *smooth transition, hedge fund, convertible arbitrage*
JEL classification: *G11, G12, C32*

1. Introduction

Academic literature on hedge fund performance has generally focused on linearly modelling the relationship between the returns of hedge funds and the asset markets and contingent claims on those assets in which hedge funds operate. Recently, several studies model the returns of these funds using techniques which are not restricted by assumptions of normality.

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We are grateful to the Irish Research Council for the Humanities and Social Sciences (IRCHSS) for research funding and SunGard Trading and Risk Systems for providing convertible bond data and pricing software.

In this paper we are interested in investigating whether an alternative non-linear model specification increases efficiency in the modelling of convertible arbitrage hedge fund returns. In particular we focus on the smooth transition autoregressive (STAR) family of models which have the advantage, over alternative non-linear regime switching specifications when modelling financial data, of allowing a smooth transition between regimes.[1]

Many studies of hedge funds have documented non-linearity in their returns (See for example, Liang (1999), Agarwal and Naik (2000), Brooks and Kat (2001), Kat and Lu (2002) and Fung and Hsieh (1997, 2000)). One avenue of research has modelled this non-linearity in a linear asset pricing framework using non-Gaussian risk factors. Fung and Hsieh (2001, 2002) present evidence of hedge fund strategy payoffs sharing characteristics with lookback straddles, and Mitchell and Pulvino (2001) document the returns from a merger arbitrage portfolio exhibiting similar characteristics to a short position in a stock index put option. Using option payoffs as risk factors, Agarwal and Naik (2004) demonstrate the non-linear relationship between hedge fund returns and risk factors. Modelling the returns of convertible arbitrage hedge funds Hutchinson and Gallagher (2007) and Agarwal, Fung, Loon and Naik (2007) construct factor portfolios mimicking convertible arbitrage investments.

In addition to the linear factor model literature several studies utilize models whose functional specification, rather than factor specification, captures the non-normal characteristics of hedge funds. Rather than specifying factors with non-normal distributions, these studies relax the assumption of a linear relationship between the risk factor and hedge fund returns. Kat and Miffre (2005) employ a conditional model of hedge fund returns which allows the risk coefficients and alpha to vary. Kazemi and Schneeweis (2003) also attempt to explicitly address the dynamics in hedge fund trading strategies by specifying conditional models of hedge fund performance. Kazemi and Schneeweis (2003) employ the stochastic discount factor model which

[1] In financial markets with many participants operating independently and at different time horizons, movements in asset prices are likely to be smooth.

has previously been employed in the mutual fund literature. Alternately, Amin and Kat (2003), imposing zero restrictions on the distribution of the funds returns, evaluate hedge funds from a contingent claims perspective.

STAR models were developed by Teräsvirsta and Anderson (1992) for modelling non-linearities in the business cycle and offer several advantages over a Hamilton (1989) Markov switching model. STAR models incorporate at least two alternate risk regimes, allowing for a smooth transition from one risk regime to another. When estimating the STAR model no *ex ante* knowledge of the threshold variable is required. These models have been specified extensively to model economic time series (see for example Sarantis (1999), Skalin and Terasvirta (1999), Ocal and Osborn (2000) and Holmes and Maghrebi (2004)) and stock returns (see for example McMillan (2001), Bradley and Jansen (2004) and Bredin and Hyde (2007)).

Overall, existing academic studies find that convertible arbitrage hedge funds generate significant abnormal returns. In studies of general hedge fund performance, Capocci and Hübner (2004) and Fung and Hsieh (2002) provide some evidence of convertible arbitrage performance. Capocci and Hübner (2004) specify a linear factor model to model the returns of several hedge fund strategies and estimate that convertible arbitrage hedge funds earn an abnormal return of 0.4% per month. Fung and Hsieh (2002) estimate the convertible arbitrage hedge fund index generates alpha of 0.7% per month. Focusing exclusively on convertible arbitrage hedge funds Hutchinson and Gallagher (2007) find evidence of individual fund abnormal performance but no abnormal returns in the hedge fund indices. Agarwal, Fung, Loon and Naik (2007) document positive abnormal returns which they account for with new issue convertible bond under pricing data.

These mixed findings suggest that either financial markets exhibit significant inefficiency in the pricing of convertible bonds, or prior studies have failed to specify a functional model which correctly explains convertible arbitrage risk. Financial theory suggests that the relationship between convertible arbitrage returns and risk factors is non-linear. Being long a convertible bond and short an underlying stock, funds are hedged against equity market risk but are left exposed to a degree of downside default and term structure risk. When the convertible bond is above a certain threshold it acts more like equity than bond. However, when the convertible bond falls in value it acts more like bond than equity. Effectively, the convertible arbitrageur is short a credit put option.[2] Highlighting this non-linearity Agarwal and Naik (2004) provide evidence that convertible arbitrage hedge fund indices' returns are positively related to the payoff from a short equity index option.

In this paper evidence is presented of a non-linear relationship between convertible arbitrage hedge fund returns and default and term structure risk factors. This non-linear relationship is modelled using logistic smooth transition autoregressive (LSTAR) models. We also provide evidence that the specification of these models provides increases in efficiency over an alternate linear specification. Nine convertible arbitrage hedge fund series are modelled, including five hedge fund indices and four portfolios made up of individual convertible arbitrage hedge funds. To ensure the robustness of these results the model is also specified for a simulated convertible arbitrage portfolio and again evidence is presented supporting the hypothesis of non-linearity in the relationship between the returns of convertible arbitrage and risk factors.

The remainder of this paper is organised as follows. The next section contains details of the data. Section 3 provides a review of the smooth transition autoregressive models. Section 4 provides details of the estimation results. Section 5 concludes.

2. Data

In this section of the paper we present details of the convertible arbitrage series and explanatory risk factors. To model the convertible arbitrage hedge fund strategy we specify five indices of convertible arbitrage hedge funds, four portfolios made up of convertible arbitrage hedge funds

[2] Some convertible arbitrage funds hold credit default swaps to hedge credit risk. However, Hutchinson and Gallagher (2007) document significant exposure amongst convertible arbitrage hedge funds to default and term structure risk factors.

from the HFR database and a simulated convertible arbitrage portfolio.[3] All of the series have different start dates. The sample period runs from the start of each series to December 2002.[4] The indices specified are the CSFB Tremont Convertible Arbitrage Index, the HFRI Convertible Arbitrage Index, the Van Hedge Convertible Arbitrage Index, the Barclay Group Convertible Arbitrage Index and the CISDM Convertible Arbitrage Index. The CSFB Tremont Convertible Arbitrage Index is an asset weighted index (rebalanced quarterly) of convertible arbitrage hedge funds beginning in 1994, the CISDM Convertible Arbitrage Index represents the median fund performance, whereas the HFRI, Van Hedge and Barclay Group Convertible Arbitrage Indices are all equally weighted indices of fund performance.

The four portfolios are: HFR EQL, an equally weighted portfolio of convertible arbitrage hedge funds; HFR LRG, an equally weighted portfolio made up of the largest funds, ranked by month *t-1* assets under management; HFR MID, an equally weighted portfolio made up of the mid ranking funds, ranked by month *t-1* assets under management; and, HFR SML, an equally weighted portfolio made up of the smallest funds, ranked by month *t-1* assets under management.

Finally CBARB, the simulated portfolio is an equally weighted portfolio constructed of long positions in convertible bonds combined with delta neutral hedged short positions in the underlying stocks. For details on the construction and statistical characteristics of this portfolio see Hutchinson and Gallagher (2006, 2007).

Descriptive statistics and cross correlations for the ten convertible arbitrage excess return series are presented in Table 1 and Table 2.[5] Of the indices the Van Hedge index has the largest mean return, 0.83, and the CSFB Tremont index has the largest variance, 1.92. The portfolios formed from the HFR database have similar mean returns but HFR SML, made up of smaller hedge funds has the largest variance, more than twice the magnitude of the other size portfolios. Finally all of the series exhibit positive kurtosis and, with the exception of the Barclay Group index, which

[3] For a review of the different hedge fund indices see Goltz, Martellini and Vaissié (2007)
[4] The number of observations for each series varies and is reported in Table 1.
[5] The one month T-bill rate is specified for the risk free return.

does not cover October 1998, negative skewness. The cumulative returns of the ten series are reported in Figure 1.

The explanatory variables specified in this study are *RMRF*, *SMB*, *HML*, *DEF* and *TERM*. Hutchinson and Gallagher (2006) provide evidence that these five equity and bond market factors drive the convertible arbitrage data generating process. *RMRF*, *SMB* and *HML* are Fama and French (1992, 1993) market, size and book-to-market factors, respectively.[6] *DEF* and *TERM* represent default and term structure risk factors (Chen, Roll and Ross (1986)). DEF_t is the difference between the overall return on a market portfolio of long-term corporate bonds minus the long term government bond return at month t. $TERM_t$ is the factor proxy for unexpected changes in interest rates. It is constructed as the difference between monthly long term government bond return and the short term government bond return. Descriptive statistics and cross correlations of the risk factors are presented in Table 3. All of the mean returns are positive. Jacque and Bera (1987) statistics indicate that four of the five risk factors exhibit non-normality. *DEF* and *TERM* exhibit autocorrelation.

In the next section of the paper we discuss the STAR methodology specified in this study to model convertible arbitrage returns.

3. Methodology

This section of the paper provides a review of threshold model methodology focusing on the smooth transition autoregressive (STAR) model first proposed by Chan and Tong (1986) and extended by Teräsvirta and Anderson (1992) for modelling non-linearity in the business cycle. STAR models are specified in this study for three principle reasons. (1) They incorporate two alternate regimes, corresponding with the theoretical relationship between convertible arbitrage returns and risk factors. One regime where the portfolio is more exposed to default and term structure risk and a second regime where the portfolio is less exposed to default and term

[6] The data on *RMRF*, *SMB* and *HML* are downloaded from Kenneth French's website.

structure risk and more exposed to the convertible arbitrage risk factor. (2) They incorporate a smooth transition from one risk regime to another. In financial markets with many participants operating independently and at different time horizons, movements in asset prices and risk weightings are likely to be smooth rather than sharp. (3) When estimating the STAR model no *ex ante* knowledge of the threshold variable level, *c*, is required. This threshold level is estimated simultaneously with the coefficients of the model. The only *ex ante* expectation of the level of the threshold is that it lies between the minimum and maximum of the threshold variable.

In this study we specify the one period lag of the convertible arbitrage series return as the threshold variable. The convertible arbitrage series proxy aggregate hedged convertible bonds held by arbitrageurs. If the series generates negative returns then aggregate hedged convertible bonds held by arbitrageurs have fallen in value. This fall in value is caused either by a decrease in the value of the short stock position in excess of the increase in the value of the long corporate bond position or, more likely, a decrease in the value of the long convertible bond position in excess of the increase in the value of the short stock position. When the one period lag of the convertible arbitrage benchmark return is below the threshold level, convertible bond prices and deltas have decreased. As convertible bond prices fall, we expect the arbitrageur's portfolio to be more exposed to default and term structure risk. When the one period lag of the convertible arbitrage benchmark return is above the threshold level, convertible bond prices and deltas increase and we expect the portfolio to exhibit less fixed income characteristics, with relatively smaller coefficients on the default and term structure risk factors.

Consider the following NLAR model.

$$y_t = \alpha' x_t + \beta' x_t f(z_t) + e_t \tag{1}$$

Where $\alpha' = (\alpha_0, \ldots, \alpha_m)$, $\beta' = (\beta_0, \ldots, \beta_m)$, $x_t = (y_t, \ldots, y_{t-p}\ ; x_{1t,\ldots}, x_{kt})$ and the variable z_t is the transition variable. If $f(\ )$ is a smooth continuous function the autoregressive coefficient ($\alpha_1 + \beta_1$) will change smoothly along with the value of y_{t-1}. This type of model is known as a smooth transition autoregressive (STAR) model. The two particularly useful forms of the STAR model that allow for a varying degree of autoregressive decay are the LSTAR (Logistic-STAR) and ESTAR (Exponential-STAR) models.

Choosing $f(z_t) = [1 + \exp(-\gamma(z_t - c))]^{-1}$ yields the logistic STAR (LSTAR) model where γ is the smoothness parameter (i.e. the slope of the transition function) and c is the threshold. In the limit as γ approaches zero or infinity, the LSTAR model becomes a linear model since the value of $f(z_t)$ is constant. For intermediate values of γ, the degree of decay depends upon the value of z_t. As z_t approaches $-\infty$, θ approaches 0 and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As z_t approaches $+\infty$, θ approaches 1 and the behaviour of y_t is given by $(\alpha' + \beta')x_t + e_t$.

Choosing $f(z_t) = 1 - \exp(-\gamma(z_t - c)^2)$ yields the exponential STAR (ESTAR) model. For the ESTAR model, as γ approaches infinity or zero the model becomes a linear model as $f(z_t)$ becomes constant. Otherwise the model displays non-linear behaviour. It is important to note that the coefficients for the ESTAR model are symmetric around $z_t = c$. As z_t approaches c, $f(z_t)$ approaches 0 and the behaviour of y_t is given by $y_t = \alpha' x_t + e_t$. As z_t moves further from c, θ approaches 1 and the behaviour of y_t is given by $(\alpha' + \beta')x_t + e_t$.

The estimation of STAR models consists of three stages (Granger and Teräsvirta (1993)):

(a) Specification of a linear model.

The initial step requires the specification of the linear model (4).

$$y_t = \alpha + \beta' x_t + \varepsilon_t \qquad (4)$$

Where y_t is the excess return on the hedge fund index, and x_t is a matrix of convertible arbitrage risk factors.

(b) Testing linearity

The second step involves testing linearity against STAR models using the linear model specified in (a) as the null. To carry out this test the auxiliary regression is estimated:

$$u_t = \beta_0' x_t + \beta_1' x_t z_t + \beta_2' x_t z_t^2 + \beta_3' x_t z_t^3 \quad (5)$$

Where the values of u_t are the residuals of the linear model specified in the first step and z_t is the transition variable. The null hypothesis of linearity is $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$.[7]

(c) Choosing between LSTAR and ESTAR

If linearity is rejected the selection between LSTAR and ESTAR models is based on the following series of nested *F* tests.

$$H3: \beta_3 = 0 \quad (6)$$

$$H2: \beta_2 = 0 | \beta_3 = 0 \quad (7)$$

$$H1: \beta_1 = 0 | \beta_2 = \beta_3 = 0 \quad (8)$$

Accepting (6) and rejecting (7) implies selecting an ESTAR model. Accepting both (6) and (7) and rejecting (8) leads to an LSTAR model as well as a rejection of (6). Granger and Teräsvirta (1993) argue that strict application of this sequence of tests may lead to incorrect conclusions and suggest the computation of the *P*-values of the *F*-tests of (6) to (8) and make the choice of the STAR model on the basis of the lowest *P*-value.

[7] Equation (5) can also be used to select the transition variable z_t. We conducted this test for each candidate for the transition variable drawing from the matrix of convertible arbitrage risk factors. As it leads to the smallest *P*-value for each of the series, we fail to reject the lag of the hedge fund series return as the choice of z_t. These results are available from the authors on request.

We estimate the STAR models using non-linear least squares in the RATS programme. RATS specifies the Marquardt variation of the Gauss-Newton to solve the non-linear least squares regression. In the next section of the paper we discuss the empirical results from our application of the STAR methodology to the convertible arbitrage series.

4. Empirical results

In this section of the paper we present the empirical results from estimating the STAR models for the ten convertible arbitrage series. The remainder of this section is divided into three subsections. Subsection 4.1 presents results from estimation of the linear model; Subsection 4.2 presents the linearity test results; and finally, Subsection 4.3 presents results from estimating the STAR models.

4.1. Linear model results

We begin with the results from estimating (9) for each of the convertible arbitrage hedge fund series.

$$y_t = \delta_0 + \delta_1 YLAG_t + \delta_2 RMRF_t + \delta_3 SMB_t + \delta_4 HML_t + \delta_5 DEF_t + \delta_6 TERM_t + \varepsilon \quad (9)$$

Where $YLAG_t$ is the one period lag of the hedge fund series return at time t. Results from estimating this model are presented in Table 4. Looking first at the equity market factors, *RMRF*, the excess return on the market portfolio is significantly positively related to five of the ten convertible arbitrage series. *SMB*, the size related factor is significantly positive for all of the funds series. This suggests that the strategy generates returns from the smaller issuers. *HML*, the book-to-market equity factor is significant for only two series, *HFR EQL* and *CBARB*. The two bond market factors, *DEF* and *TERM*, are significantly positive for nine of the ten hedge fund series. HFR SML is the only series with no exposure to these factors. Finally, *YLAG* is significant for eight of the ten convertible arbitrage series. Seven of the hedge fund series exhibit significantly positive alphas, ranging from 15 to 41 basis points per month. This finding of abnormal performance for the convertible arbitrage strategy from a linear specification is consistent with prior studies.

The explanatory power of the linear model (adjusted R^2) ranges from 8% for HFR SML to 59% for the CISDM series. Jacque and Bera statistics indicate seven of the ten series residuals are significantly non-normal, and we fail to reject ARCH effects for all of the estimated regression residuals.

4.2 Linearity tests

The linearity tests for each of the series are displayed in Table 5. To ensure that the most appropriate lag of the convertible arbitrage series is specified as the transition variable we begin by setting $z_t = y_{t-d}$ where d is the delay parameter. We then conduct linearity tests for values of the delay parameter over the range $1 \leq d \leq 8$. *P*-values for the linearity test are calculated and displayed in row one of each panel in Table 5. The delay parameter d is chosen by the lowest *P*-value. The tests for the choice between ESTAR and LSTAR for each series are shown in rows 2 to 4 of each Panel in Table 5.

Linearity tests of the HFRI index are reported in Panel A of Table 5. Linearity is rejected at levels of d = 1, 2, 3 and 8 but the lowest *P*-value is for d = 1 so, consistent with expectations, y_{t-1}, the one period lag of the hedge fund series return, is chosen as the transition variable z_t. At d = 1, the only significant *P*-value is for H_1 indicating an LSTAR model.

For each of the other convertible arbitrage series we find evidence to reject linearity at multiple lags. Consistent with our finding for HFRI, the lowest *P*-value for each series is for d = 1. Choosing between ESTAR and LSTAR models for each series is not as straightforward. CSFB, VANHEDGE, BRCLYGRP, HFL LRG and HFR MID are all LSTAR. For CISDM and HFR EQL at d = 1, the lowest *P*-value is for H_1, again indicating an LSTAR model. Finally, as the result for CBARB is less conclusive we assume it follows an LSTAR specification consistent with the other nine convertible arbitrage series. In the next subsection we present results from estimation of the LSTAR models.

4.3 Smooth transition autoregressive model

The LSTAR model parameter estimates together with the diagnostic statistics are reported in Table 6. Figure 2 displays the transition functions plotted against time and the transition variable. We identify two regimes which we term the 'negative alpha' regime and the 'positive alpha regime'. The transition between the two regimes is relatively smooth ($3.92 < \gamma < 9.14$). The level of the threshold lies between +0.33 for the HFRI series and -1.64 for the CBARB series.

Looking at Fig. 2 there are several distinct periods when the convertible arbitrage series move into the negative alpha regime, 1990 to 1992; 1994; 1998; and, 2001 to 2002. These coincide with severe financial events which are likely to have negatively affected credit spreads. 1990 to 1992 coincides with the collapse of the Exchange Rate Mechanism (ERM) in the Eurobloc; 1994 coincides with the Mexican Peso crisis; 1998 coincides with the Asian and Long Term Capital Management crises; and finally, 2001 to 2002 coincides with the ending of the dotcom bubble and the Argentina financial crisis.

Examining the coefficient estimates in Table 6, with the exception of HFR SML which has no exposure to these risk factors, coefficients on *DEF* and *TERM* decrease markedly as the series switches from the negative alpha regime to the positive alpha regime. There is no clear pattern for the remaining risk factors. The equity market factors are not significant in either regime for four of the series (HFRI, VanHedge, CISDM and HFR EQL) and only one coefficient is significant in each state for three series (BRCLYGRP, HFR LRG and CBARB). HFR MID and HFR SML have large exposure to the three equity market risk factors, *RMRF*, *SMB* and *HML* in the negative alpha regime and this exposure decreases markedly in the positive alpha regime.

Finally, for the CSFB series the equity market factors show no clear pattern, with *RMRF* and *HML* coefficients increasing and the *SMB* coefficient decreasing in the positive alpha regime.

The specification of the LSTAR models improves efficiency over the linear specification for all of the convertible arbitrage series with adjusted R^2 range from 45% to 71%. There is also a reduction in AIC and SBC for all of the series. ρ^* the ratio of residual standard deviations of the LSTAR and linear models demonstrates the efficiency gain from the LSTAR specification.[8] This ratio ranges from 0.54 for the HFR SML series to 0.88 for the CBARB and VANHEDGE series.[9] For six of the series we can now reject the presence of ARCH effects in the residuals, although there remains evidence of non-normality in seven of the series.

Consistent with theoretical expectations, the results for all of the convertible arbitrage series provide evidence to support the existence of a non-linear relationship between convertible arbitrage returns and explanatory risk factors. We identify two alternate risk regimes for the strategy; a negative alpha regime; and, a positive alpha regime.

In the negative alpha regime, with $z_t < c$ (i.e. prior month convertible arbitrage returns are below the threshold level) the convertible arbitrage series have increased risk coefficients and negative alpha. In this regime the portfolio generally exhibits increased exposure to fixed income risks. This regime also appears to coincide with incidences of market stress, with a corresponding decrease in liquidity, such as the 1994 Peso crisis and the 1998 Asian currency crisis.

In the positive alpha regime, with $z_t > c$ (i.e. prior month convertible arbitrage returns are above the threshold level) the default and term structure risk coefficients generally decrease and the strategy exhibits positive alpha. In this regime the portfolio exhibits less fixed income risk characteristics and is characterised by relatively benign financial markets.

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[8] ρ^* the ratio of the residual standard deviations is calculated as σ_{nl}/σ_{lin}, where σ_{nl} is the LSTAR estimated residual standard deviation and σ_{lin} is the residual standard deviation from the estimated linear model. The smaller the ρ^* the greater the efficiency gain.

[9] The smaller the ρ^* the greater the efficiency gain.

The presence of these two risk regimes has important implications for investors in convertible arbitrage hedge funds. Though these funds have historically offered high returns with relatively low standard deviation and exposure to market risk factors, this appears due to the favourable market conditions since 1990. The evidence presented in this paper indicates that in future periods of market stress the strategy will become significantly exposed to fixed income risk factors, and, more importantly, under-perform a passive investment in these factors.

5. Conclusions

The tests conducted in this paper have rejected linearity for the convertible arbitrage hedge fund series. These hedge fund series are classified as logistic smooth transition autoregressive (LSTAR) models. The estimated LSTAR models provide a satisfactory description of the non-linearity found in convertible arbitrage hedge fund returns and have superior explanatory power relative to linear models. For all of the hedge fund series the estimated LSTAR model improves efficiency relative to the linear alternative.

The estimates of the transition parameter indicate that the speed of transition is relatively slow from one regime to another but the factor loadings become relatively large, and alphas become negative, as previous month's hedge fund returns move below the threshold level. Historically the switch into the negative alpha regime coincides with several severe financial crises.

We make two key contributions to the understanding of convertible arbitrage and hedge fund risk and returns in this paper. We identify two risk regimes and we also identify market conditions where arbitrageurs under-perform.

Previous research has identified only one risk regime for convertible arbitrage. The evidence presented here supports the existence of two alternate risk regimes, a negative alpha regime, with higher default and term structure risk when month *t-1* returns are below a threshold level, and a positive alpha regime, with lower default and term structure risk when month *t-1* returns are above a threshold level.

Prior research has also documented the strategy generating either significantly positive alpha or alpha insignificant from zero. Our finding of negative alpha in the higher risk regime is important for investors in convertible arbitrage hedge funds. While convertible arbitrageurs outperform a passive investment in risk factors in relatively benign financial markets, when arbitrageurs are more exposed to default and term structure risk, they can under-perform relative to a passive investment in the risk factors.

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Table 1

Convertible arbitrage series summary statistics

This table reports summary statistics for the monthly convertible arbitrage excess return series specified in this analysis. HFRI is the HFR Convertible Arbitrage Index of hedge funds, CSFB is the CSFB Tremont Convertible Arbitrage Index of hedge funds, VANHEDGE is the VanHedge Convertible Arbitrage Index of hedge funds, BRCLY GRP is the Barclay Group Convertible Arbitrage Index of hedge funds and CISDM is the CISDM Convertible Arbitrage Index of hedge funds. HFR EQL is an equally weighted portfolio of convertible arbitrage hedge funds from the HFR database, HFR LRG, HFR MID & HFR SML are equal weighted portfolios of large, medium and small size (assets under management) convertible arbitrage hedge funds from the HFR database. CBARB is a simulated convertible arbitrage portfolio. N is the number of observations. JB Stat is the Jacque-Bera normality test statistic. Q-Stat is the Ljung-Box autocorrelation test Q Statistic for twelve lags of each series. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

	N	Mean	Variance	Skewness	Kurtosis	JB Stat	Q Stat
HFRI	156	0.55	0.98	-1.37	3.12	112.32***	99.99***
CSFB	108	0.45	1.92	-1.69	4.34	136.07***	59.84***
VANHEDGE	96	0.83	0.78	-0.63	2.14	24.70***	30.25***
BRCLY GRP	48	0.79	0.81	0.13	1.47	4.43	18.78*
CISDM	131	0.65	0.45	-1.14	4.03	117.78***	54.11***
HFR EQL	156	0.60	0.98	-0.60	0.45	10.79***	76.87***
HFR LRG	129	0.54	1.11	-1.27	2.96	81.95***	46.96***
HFR MID	129	0.59	0.99	-1.44	6.19	255.93***	40.75***
HFR SML	129	0.69	2.46	-0.62	5.20	157.08***	30.42***
CBARB	156	0.33	3.10	-1.36	9.00	573.96***	62.37***

Table 2
Convertible arbitrage series correlation matrix

This table reports linear correlation coefficients for the monthly convertible arbitrage excess return series in this analysis. HFRI is the HFR Convertible Arbitrage Index of hedge funds, CSFB is the CSFB Tremont Convertible Arbitrage Index of hedge funds, VANHEDGE is the VanHedge Convertible Arbitrage Index of hedge funds, BRCLY GRP is the Barclay Group Convertible Arbitrage Index of hedge funds and CISDM is the CISDM Convertible Arbitrage Index of hedge funds. HFR EQL is an equally weighted portfolio of convertible arbitrage hedge funds from the HFR database, HFR LRG, HFR MID & HFR SML are equal weighted portfolios of large, medium and small size (assets under management) convertible arbitrage hedge funds from the HFR database. CBARB is a simulated convertible arbitrage portfolio.

	HFRI	CSFB	VAN HEDGE	BRCLY GRP	CISDM	HFR EQL	HFR LRG	HFR MID	HFR SML	CBARB
HFRI	1.00	0.76	0.94	0.95	0.41	0.92	0.92	0.90	0.74	0.53
CSFB		1.00	0.74	0.73	0.43	0.76	0.82	0.73	0.57	0.33
VAN HEDGE			1.00	0.97	0.37	0.91	0.90	0.87	0.76	0.55
BRCLY GRP				1.00	0.38	0.95	0.94	0.91	0.78	0.59
CISDM					1.00	0.33	0.48	0.37	0.10	0.26
HFR EQL						1.00	0.94	0.94	0.89	0.54
HFR LRG							1.00	0.88	0.71	0.54
HFR MID								1.00	0.75	0.55
HFR SML									1.00	0.41
CBARB										1.00

Table 3
Risk factor summary statistics and correlation matrix

This table reports summary statistics and linear correlation coefficients for monthly financial variables. Panel A reports the summary statistics, while Panel B reports linear correlations. RMRF, SMB and HML are factors representing market, size and book-to-market risk premia (Fama and French, 1992). DEF and TERM are risk factors for default and term structure risk (Chen, Roll and Ross, 1986). JB Stat is the Jacque-Bera normality test statistic. Q-Stat is the Ljung-Box autocorrelation test Q Statistic for twelve lags of each series. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively.

Panel A: Summary statistics

	Mean	Variance	Skewness	Kurtosis	JB Stat	Q Stat
RMRF	0.49	20.39	-0.61	0.57	11.66***	21.67
SMB	0.15	12.72	0.45	1.72	24.49***	22.95
HML	0.10	18.03	-0.64	5.58	212.90***	23.96
DEF	0.54	9.39	-0.38	2.59	47.20***	53.32***
TERM	0.11	5.82	-0.36	0.22	3.65	37.93**

Panel B: Correlation matrix

	RMRF	SMB	HML	DEF	TERM
RMRF	1.00	0.19	-0.34	0.35	0.09
SMB		1.00	-0.37	0.36	-0.16
HML			1.00	0.06	-0.06
DEF				1.00	-0.68
TERM					1.00

Table 4

Linear AR(1) Model

This table reports the OLS estimation of the linear first order autoregressive model. YLAG is the one period lag of the dependent variable. ***, ** and * indicate coefficient significance at the 1%, 5% and 10% levels respectively. σ is the residual standard deviation, Adj. R^2 is the adjusted R^2. JB is the Jacque-Bera test for normality and ARCH(4) is the LM test up to lag 4. JB and ARCH test results are P-Values. AIC and SBC are the Akraike Information Criterion and the Schwartz Bayesian Criterion respectively.

Variable	HFRI	CSFB	VANHEDGE	BRCLY GRP	CISDM	HFR EQL	HFR LRG	HFR MID	HFR SML	CBARB
δ_0	0.15**	0.09	0.32***	0.41***	0.23***	0.29***	0.14	0.31***	0.46**	0.15
δ_{YLAG}	0.52***	0.61***	0.51***	0.42***	0.51***	0.35***	0.52***	0.32***	0.22	0.09
δ_{RMRF}	0.02*	-0.01	0.02	0.03*	0.04***	0.06***	-0.01	0.02	0.03	0.14***
δ_{SMB}	0.04**	0.05*	0.05**	0.06*	0.04***	0.07***	0.04*	0.06***	0.07**	0.08***
δ_{HML}	0.00	0.00	0.00	0.03	0.01	0.03*	0.02	0.01	0.01	0.06***
δ_{DEF}	0.16***	0.26**	0.16***	0.10***	0.08***	0.08**	0.22***	0.10*	0.07	0.17***
δ_{TERM}	0.20***	0.28***	0.19***	0.15***	0.12***	0.16***	0.23***	0.18***	0.09	0.24***
Diagnostics										
σ	0.20	0.46	0.18	0.22	0.08	0.26	0.30	0.34	1.09	0.68
Adj. R^2	0.55	0.49	0.51	0.37	0.59	0.44	0.45	0.25	0.08	0.41
JB	0.00	0.00	0.02	0.75	0.00	0.12	0.12	0.00	0.00	0.05
ARCH(4)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AIC	653.80	504.28	348.98	155.46	418.50	691.32	567.16	600.78	754.10	841.50
SBC	675.10	522.99	366.85	168.41	438.63	712.63	587.13	620.91	774.23	862.81

Table 5
Linearity and STR tests

This table presents results from a sequence of *F*-tests carried out for each of the convertible arbitrage series after estimation of the following auxiliary regression,

$$u_t = \beta_0 z_t + \beta_1 z_t x_t + \beta_2 z_t x_t^2 + \beta_3 z_t x_t^3$$

Where the values of u_t are the residuals from the linear AR(d) model $y_t = \alpha_0 + \theta y_{t-d} + \lambda' x_t + u_t$. The null hypothesis of linearity is $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$. The selection between L-STAR and E-STAR models is based on the following series of nested *F*-tests.

$$H_3 : \beta_3 = 0$$
$$H_2 : \beta_2 = 0 | \beta_3 = 0$$
$$H_1 \; \beta_1 = 0 | \beta_2 = \beta_3 = 0$$

***, ** and * indicate coefficient significance at the 1%, 5% and 10% levels respectively.

Panel A: HFRI								
D	1	2	3	4	5	6	7	8
H_0	0.01**	0.03**	0.08*	0.43	0.33	0.85	0.46	0.10*
H_3	1.00	0.20	0.16	0.88	0.25	0.72	0.96	0.49
H_2	0.19	0.31	0.07*	0.28	0.62	0.90	0.07*	0.11
H_1	0.00***	0.01***	0.42	0.18	0.25	0.40	0.53	0.10
Panel B: CSFB TREMONT								
D	1	2	3	4	5	6	7	8
H_0	0.00***	0.00***	0.15	0.95	0.99	0.75	0.52	0.92
H_3	0.50	0.26	0.55	0.86	0.96	0.84	0.10*	0.77
H_2	0.76	0.64	0.52	0.91	0.98	0.18	0.64	0.61
H_1	0.00***	0.00***	0.02**	0.56	0.67	0.92	0.97	0.87
Panel C: VANHEDGE								
D	1	2	3	4	5	6	7	8
H_0	0.00***	0.00***	0.00***	0.24	0.53	0.01***	0.81	0.09*
H_3	0.55	0.29	0.00***	0.14	0.69	0.01***	0.77	0.35
H_2	0.92	0.45	0.02**	1.00	0.18	0.13	0.65	0.80
H_1	0.00***	0.00***	0.07*	0.06*	0.65	0.49	0.51	0.01***
Panel D: BRCLYGRP								
D	1	2	3	4	5	6	7	8
H_0	0.08*	0.16	0.13	0.51	0.79	0.13	0.61	0.80
H_3	0.62	0.98	0.38	0.49	0.71	0.83	0.19	0.57
H_2	0.70	0.69	0.09*	0.41	0.57	0.00***	0.99	0.82
H_1	0.00***	0.00***	0.10	0.47	0.60	0.78	0.59	0.55
Panel E: CISDM								
D	1	2	3	4	5	6	7	8
H_0	0.00***	0.02**	0.33	0.00***	0.44	0.85	0.78	0.07*
H_3	0.06*	0.10*	0.16	0.19	0.57	0.54	0.29	0.19
H_2	0.14	0.64	0.49	0.03**	0.09*	0.49	0.75	0.75
H_1	0.00***	0.00***	0.53	0.01**	0.89	0.97	0.91	0.02**
Panel F: HFR EQL								
D	1	2	3	4	5	6	7	8
H_0	0.00***	0.14	0.12	0.03**	0.36	0.58	0.95	0.57
H_3	0.46	0.81	0.17	0.42	0.40	0.52	0.66	0.92
H_2	0.08*	0.69	0.24	0.03**	0.13	0.32	0.96	0.32
H_1	0.00***	0.01***	0.24	0.10*	0.77	0.69	0.70	0.28

Table 5. Continued.

Panel G: HFR LRG								
D	1	2	3	4	5	6	7	8
H_0	0.00***	0.00***	0.07*	0.53	0.16	0.49	0.94	0.44
H_3	0.21	0.48	0.59	0.13	0.16	0.50	0.42	0.55
H_2	0.28	0.59	0.01**	0.89	0.22	0.32	0.95	0.63
H_1	0.00***	0.00***	0.32	0.62	0.39	0.53	0.94	0.16
Panel H: HFR MID								
D	1	2	3	4	5	6	7	8
H_0	0.01**	0.58	0.17	0.13	0.09*	0.85	0.86	0.98
H_3	0.27	0.92	0.06*	0.30	0.79	0.50	0.91	0.90
H_2	0.51	0.58	0.61	0.05**	0.05*	0.91	0.51	0.81
H_1	0.00***	0.13	0.37	0.57	0.07*	0.63	0.61	0.89
Panel I: HFR SML								
D	1	2	3	4	5	6	7	8
H_0	0.00***	0.00***	0.00***	0.01**	0.00***	0.04**	0.00***	0.18
H_3	0.02**	0.00***	0.46	0.05**	0.01***	0.22	0.01***	0.17
H_2	0.00***	0.25	0.00***	0.24	0.08*	0.01***	0.33	0.31
H_1	0.01***	0.23	0.02**	0.04**	0.12	0.83	0.04**	0.33
Panel J: CBARB								
D	1	2	3	4	5	6	7	8
H_0	0.00***	0.26	0.66	0.01***	0.30	0.01**	0.01***	0.00***
H_3	0.03**	0.11	0.72	0.11	0.36	0.00***	0.30	0.03**
H_2	0.07*	0.27	0.35	0.00***	0.74	0.39	0.00***	0.03**
H_1	0.15	0.79	0.59	0.28	0.10*	0.99	0.69	0.02**

Table 6
Smooth transition autoregressive regression model

This table reports the non-linear least squares (NLLS) estimation of the smooth transition autoregressive model,

$$y_t = \alpha' x_t + F(z_t)\beta' x_t + e_t\,;\; F(z_t) = \{1 + exp[-\gamma(z_t - c)]\}^{-1}\;;\text{ where } \gamma > 0$$

***, ** and * indicate coefficient significance at the 1%, 5% and 10% levels respectively. σ is the residual standard deviation, Adj. R^2 is the adjusted R^2. JB is the Jacque-Bera test for normality and ARCH(4) is the LM test up to lag 4. JB and ARCH test results are P-Values. ρ^* demonstrates the efficiency gain. It is computed as σ_{NL}/σ_L where σ_{NL} and σ_L is the residual standard deviation from the non-linear and linear models respectively. AIC and SBC are the Akraike Information Criterion and the Schwartz Bayesian Criterion respectively.

Variable	HFRI	CSFB	VANHEDGE	BRCLYGRP	CISDM	HFR EQL	HFR LRG	HFR MID	HFR SML	CBARB
α_0	-0.04	-0.29	-0.33	-0.18	-0.17	-0.22	-0.35	-1.33**	-2.32	-1.67**
α_{YLAG}	0.49***	0.44**	0.65	1.82***	0.35*	0.39**	0.32*	0.02	-0.54	-0.10
α_{RMRF}	0.03	-0.14**	0.00	0.06	0.03	0.03	-0.21***	0.28*	0.95**	0.28*
α_{SMB}	0.05	0.20***	-0.10	0.23**	0.05	0.06	0.05	0.87***	0.83***	-0.09
α_{HML}	-0.03	-0.14**	0.02	0.04	0.05	0.00	-0.04	0.76***	2.60***	-0.20
α_{DEF}	0.29***	0.57***	0.75***	0.43**	0.29***	0.30***	0.68***	0.69***	-0.78	0.39
α_{TERM}	0.36***	0.63***	0.44**	0.84***	0.28***	0.44***	0.64***	0.86***	-1.27	0.49**
β_0	0.57**	0.35	0.69	0.79	0.76***	0.13	0.74**	1.70**	2.88	1.98**
β_{YLAG}	-0.20	0.27	-0.16	-1.51***	-0.12	-0.01	0.09	0.28	0.72*	0.08
β_{RMRF}	-0.01	0.16*	0.03	-0.05	0.00	0.03	0.23***	-0.25*	-0.93**	-0.17
β_{SMB}	0.00	-0.16*	0.13	-0.22**	-0.02	0.01	-0.02	-0.82***	-0.77**	0.17
β_{HML}	0.04	0.16**	-0.03	-0.04	-0.04	0.03	0.07	-0.75***	-2.62***	0.26*
β_{DEF}	-0.26**	-0.50***	-0.66***	-0.35	-0.28***	-0.32***	-0.64***	-0.66***	0.87	-0.25
β_{TERM}	-0.27**	-0.52***	-0.31	-0.71***	-0.22**	-0.42***	-0.57***	-0.75***	1.34	-0.28
c	0.33***	0.19	-0.27**	0.07	0.16*	0.21	0.23**	-0.78***	-1.40***	-1.64***
γ	7.33**	3.92**	6.10***	6.37***	8.17***	5.72**	6.82***	9.14*	6.51***	3.96***
Diagnostics										
σ	0.17	0.28	0.16	0.14	0.08	0.21	0.22	0.26	0.59	0.60
R^2	0.64	0.65	0.69	0.70	0.71	0.55	0.62	0.45	0.48	0.50
JB	0.28	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.01	0.09
ARCH(4)	0.65	0.53	0.00	0.00	0.01	0.18	0.39	0.98	0.00	0.21
ρ^*	0.83	0.60	0.88	0.64	0.95	0.83	0.75	0.78	0.54	0.88
AIC	612.51	460.05	300.17	114.71	366.14	650.80	514.14	555.13	672.98	810.00
SBC	615.56	462.72	302.73	116.56	369.01	653.84	516.99	558.01	675.86	813.04

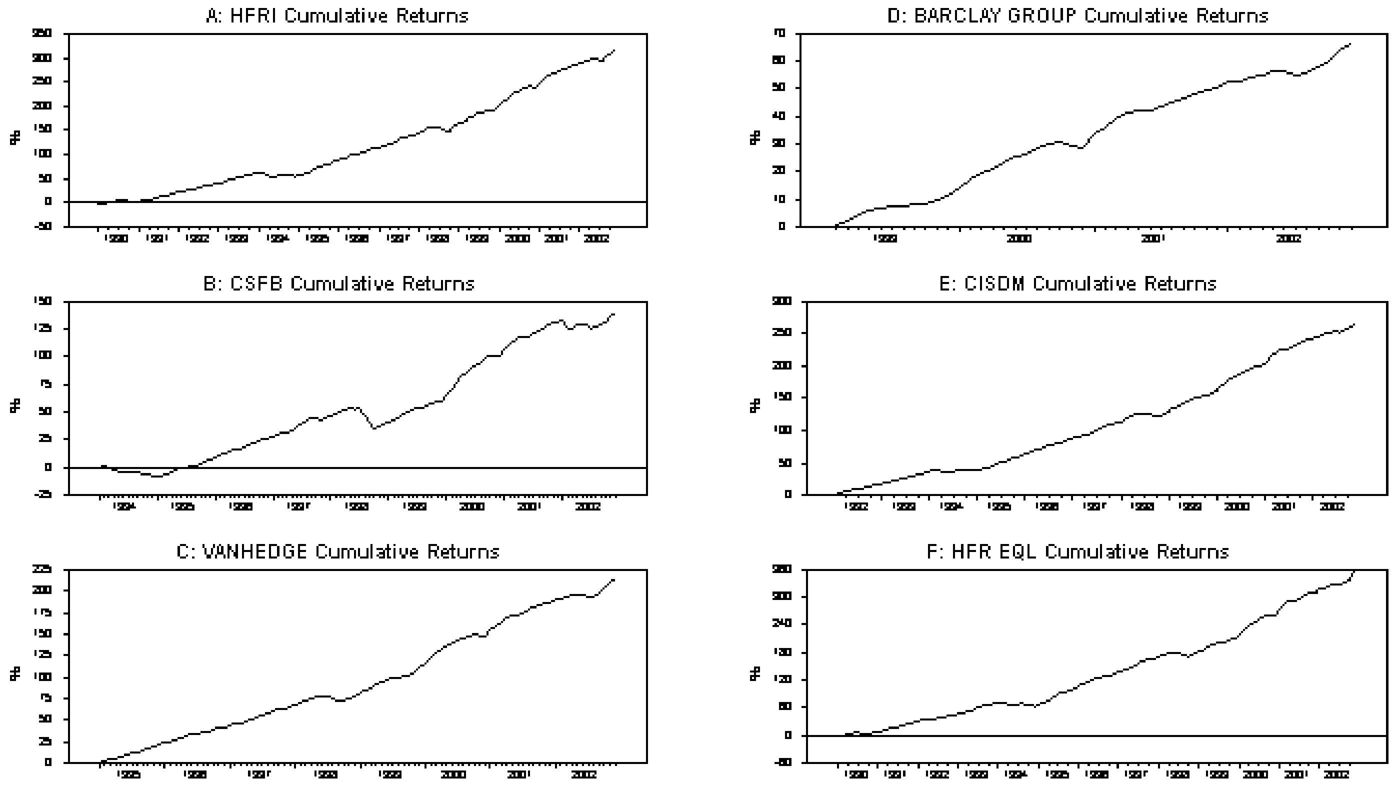

Fig. 1. Cumulative Returns of the convertible arbitrage series

This figure plots the cumulative returns for each of the convertible arbitrage series over the sample period.

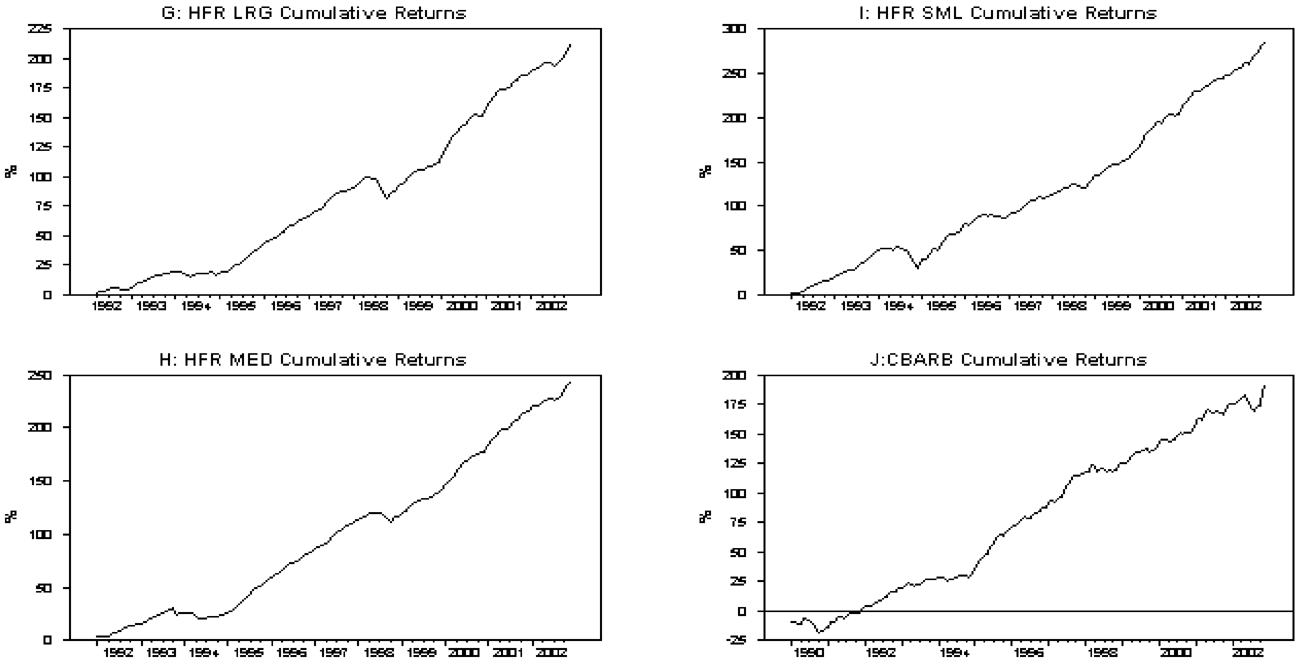

Fig. 1. Continued

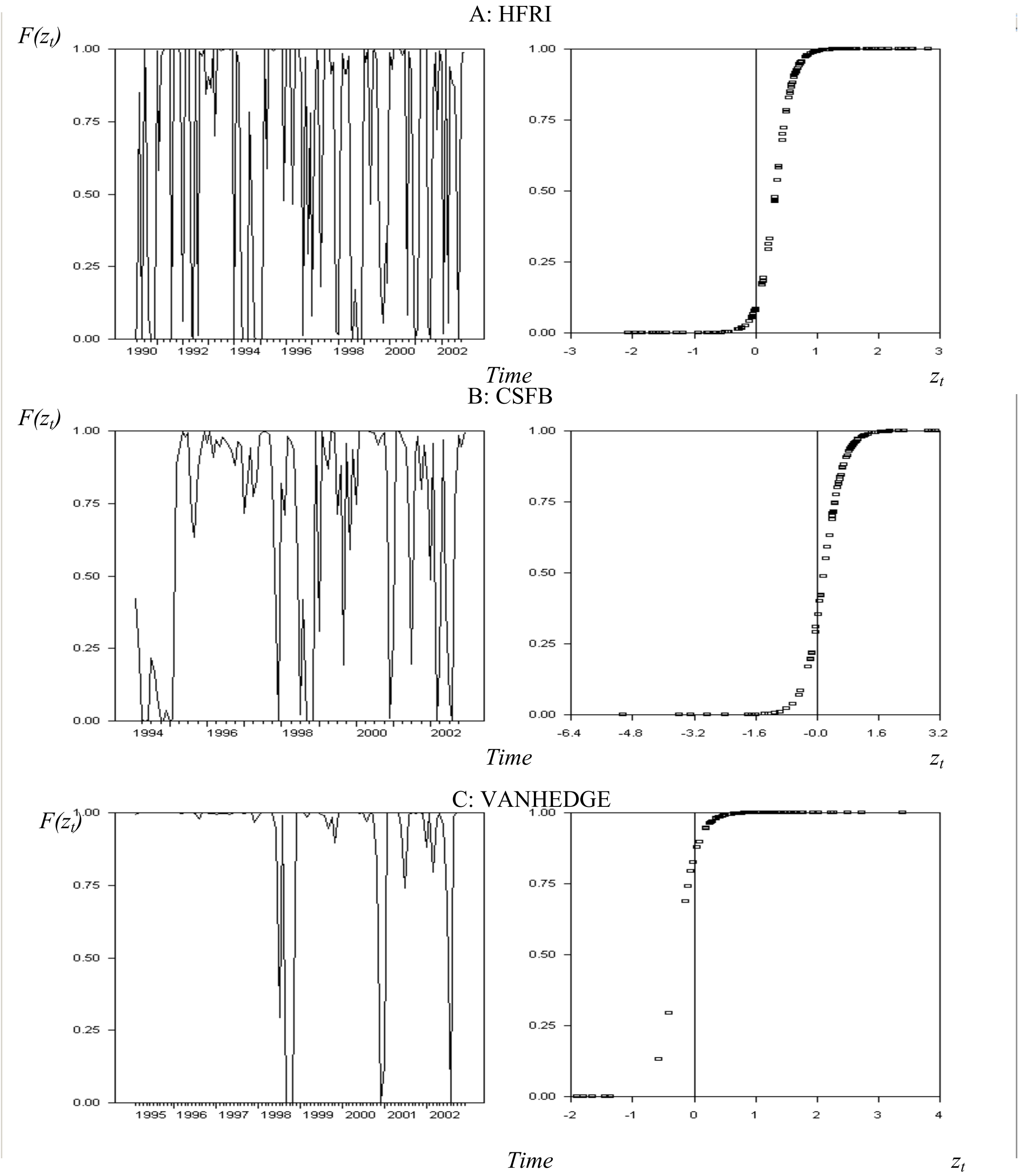

Fig 2. Transition function for the smooth transition autoregressive (STAR) models

Left hand panel plots the transition function $f(z_t)$ against time. Right hand panel plots $f(z_t)$ against the transition variable z_t for each of the convertible arbitrage series.

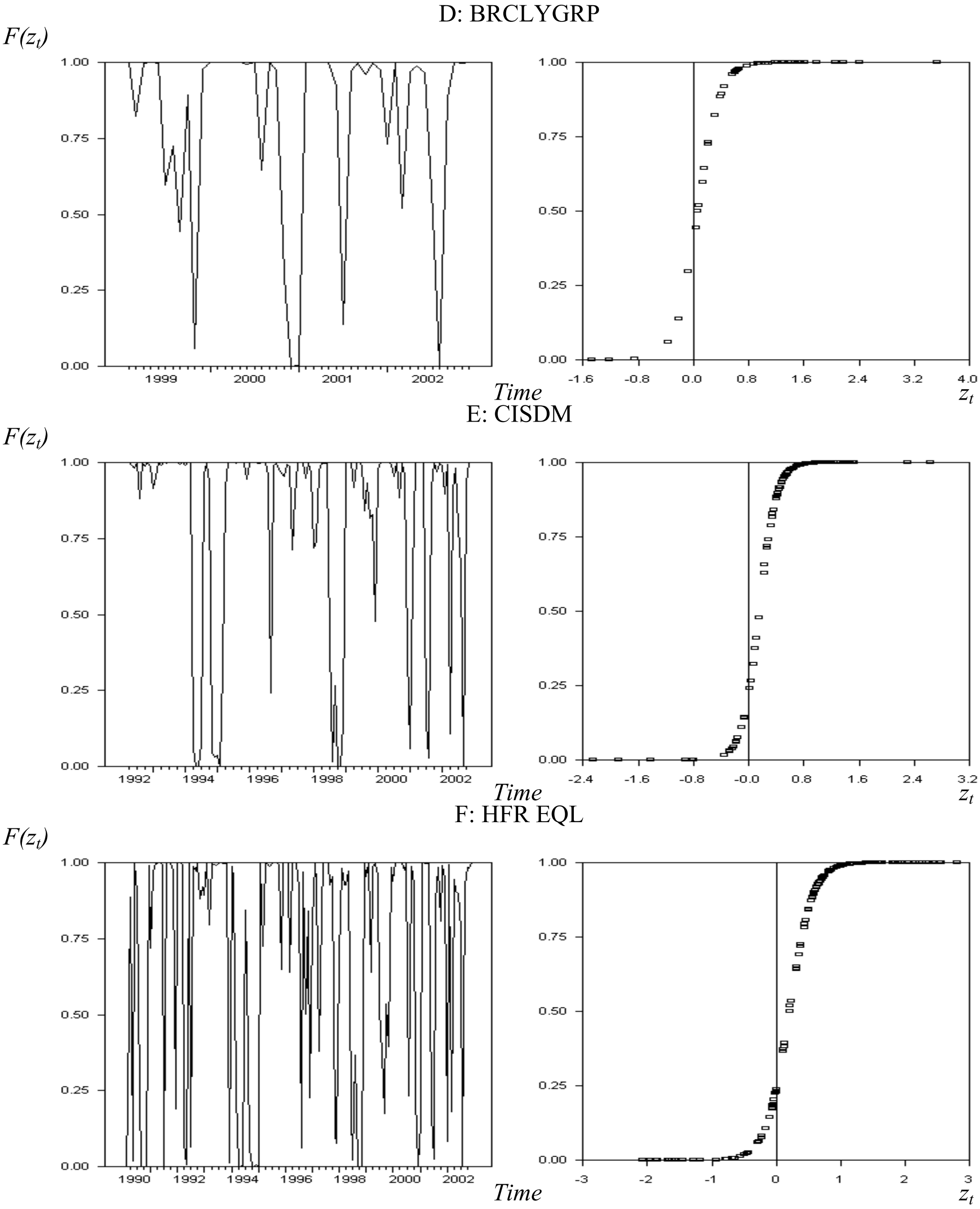

Fig 2. Continued.

G: HFR LRG

H: HFR MID

I: HFR SML

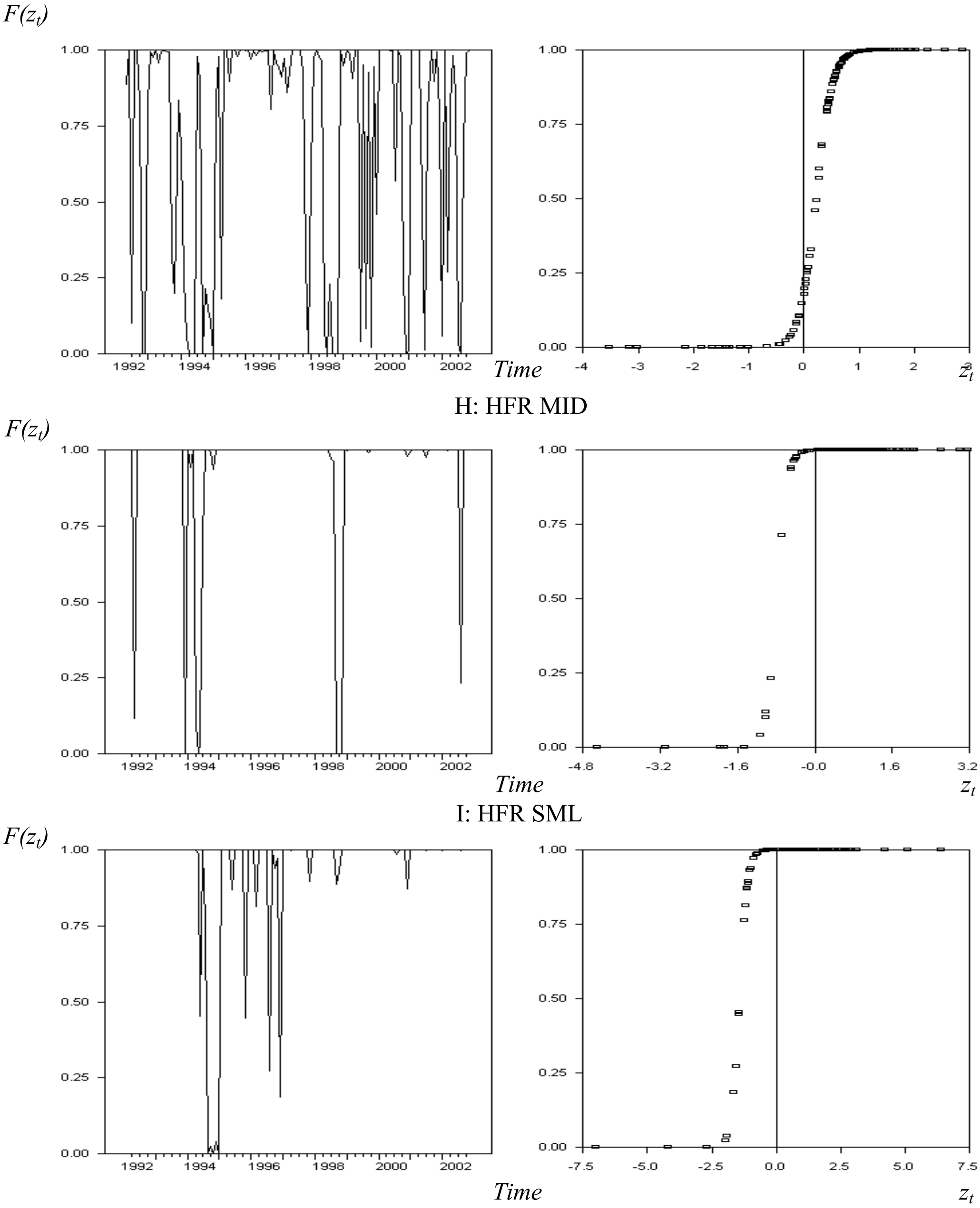

Fig 2. Continued.

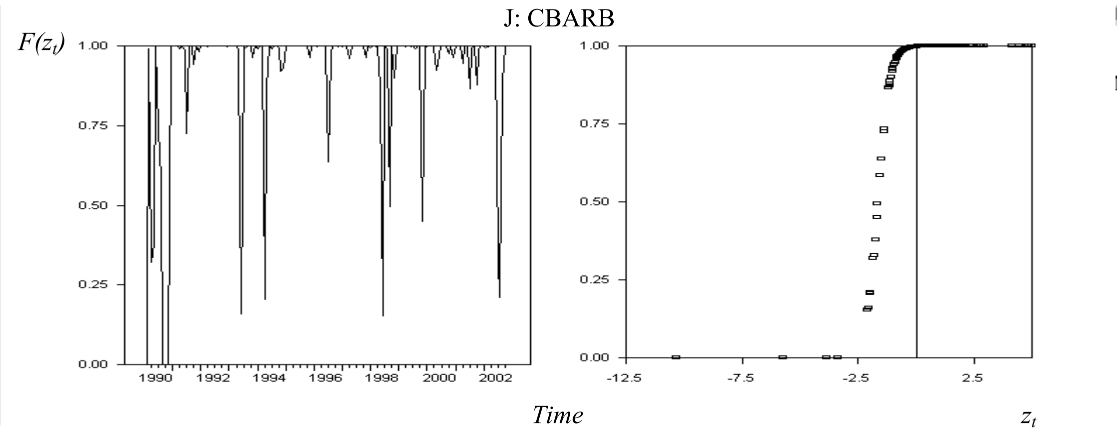

Fig 2. Continued.