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Robert J. Bianchi, Michael E. Drew and Thanula R. Wijeratne

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Systemic Risk, the TED Spread and Hedge Fund Returns

Robert J. Bianchi, Michael E. Drew^{*} and Thanula R. Wijeratne

Department of Accounting, Finance and Economics

Griffith Business School

Griffith University

Nathan, Queensland, 4111

Australia

Abstract

This study examines the effects of systemic risk on global hedge fund returns. We consider systemic risk as a conditional information variable to predict the underlying exposures to various asset market returns and risk factors. This study examines a proxy for global systemic risk employed by investment professionals known as the Treasury/Eurodollar (TED) spread. The findings reveal that increases in systemic risk causes some hedge fund investment styles to dynamically reduce their equity and stock momentum exposures while others increase their exposures to investment grade bonds and commodities. The information content of systemic risk via the TED spread assists us in better understanding the behaviour of global hedge fund returns.

* Corresponding author: Email: michael.drew@griffith.edu.au; Tel: +61-7-3735 5311; Fax: +61-7-3735 3719.

1. Introduction

The unfolding global financial crisis (GFC) and the events leading up to it have increased the attention of global hedge funds and their role in systemic risk. Systemic risk in the finance literature has been synonymous with hedge funds since the near collapse of Long Term Capital Management (LTCM) in 1998. The President's Working Group of Financial Markets (1999), Edwards (1999) and Chan, Getmansky, Haas and Lo (2006) have all concluded that LTCM and the global hedge fund industry significantly increased the level of systemic risk in 1998. Opposing literature from Eichengreen and Mathieson (1998a, 1998b) and Eichengreen and Mathieson, Chadha, Jansen, Kodres and Sharma (1998), Fung and Hsieh (2000) and Ferguson and Laster (2007) argue that hedge funds are not responsible for major market turmoil and therefore contribute little to systemic risk. Given this controversy, the association between hedge funds and systemic risk remains unclear. This paper seeks to explore systemic risk as an information variable to better understand the behaviour of global hedge fund returns.

This study does not focus on the causes of systemic risk as it has been covered elsewhere in the finance and economics literature including De Bandt and Hartmann (2000) and the IMF (2009). This study considers whether changes in systemic risk can explain global hedge fund returns. Previous studies by Fung and Hsieh (2004), Capocci and Hubner (2004) and Bianchi, Drew and Stanley (2008) have demonstrated that the sources of hedge fund returns can, at times, be related to conventional market returns and risk factors of various asset markets. In a related strand of literature, Amenc, El Bied and Martellini (2003) and Hamza, Kooli and Roberge (2006) suggest that hedge fund returns are predictable by employing market related returns and risk factors. Other studies in the mutual fund literature by Fama and French (1989), Ferson and Harvey (1991) and Chen (1991) argue that predictability in stock returns arises as a result of time-varying compensation for stages in the business cycle. This study integrates the above literature by examining systemic risk as a conditioning variable and considers whether global hedge fund returns reflect time-varying compensation for systemic risk.

As stated in IMF (2009), the term 'systemic risk' is notoriously difficult to define and measure. In this study, we contribute to the literature by employing a well recognised proxy for systemic risk employed by investment professionals which is known as the Treasury/Eurodollar (TED) spread. The TED spread is the difference between the 3 month LIBOR rate on Eurodollars and the 3 month U.S Treasury bill rate. We examine whether changes in this proxy for global systemic risk provides information in predicting global hedge fund returns.

The following paper explores three key ideas. First, we examine systemic risk as an explanatory variable for global hedge fund returns. Second, we employ the TED spread as a proxy for global systemic risk. Finally, we examine systemic risk in the form of the TED spread as a conditioning variable which may explain hedge fund returns via its interaction with independent variables. The

main findings of this study reveal that some hedge fund investment styles reduce their equity and stock momentum exposure when systemic risk increases. At the same time, other hedge funds increase their exposures to investment grade bonds and commodities. It is our conjecture that systemic risk via the TED spread is an information variable which can assist in better understanding the behaviour of global hedge fund returns.

2. Related literature

Systemic risk, while being largely undefined, often refers to macroeconomic shocks or events that destabilise the macroeconomy. Studies such as Bhansali, Gingrich and Longstaff (2008), Das and Uppal (2004), Huang, Zhou and Zhu (2009) and Lehar (2005) demonstrate the destabilising effects that systemic risk imposes on equity and credit markets. Whilst voluminous literature has examined the impact of systemic risk on assets, credit markets and banks, little research attention has been given to the impact of systemic risk on global hedge fund returns.

Studies by Bianchi *et. al.*, (2008), Capocci and Hubner (2004) and Fung and Hsieh (2004) have demonstrated that some hedge fund styles exhibit low market related exposures while other hedge fund investments exhibit high beta exposure to various markets and risk factors. Although these studies measure the source of hedge fund returns, they remain silent on whether hedge fund returns themselves are affected by global systemic risk.

One of the first studies to examine the relationship between systemic risk and hedge funds comes from Fung and Hsieh (2000) who examine historical moments of market turmoil. Fung and Hsieh (2000) demonstrate that hedge funds do not cause or contribute to these destabilising financial market events. In another study, Chan, Getmansky, Haas and Lo (2005) explicitly examine hedge funds and systemic risk. Chan *et. al.*, (2005) refer to systemic risk as the possibility of a series of correlated defaults, such as bank runs, that occur over a short period of time, usually caused by a single major event. The research motivation stems from the LTCM collapse, which caused considerable stress on global financial markets. The focus of Chan *et. al.*, (2005) is the relationship between illiquidity in the hedge fund industry and macroeconomic shocks in global markets. Employing the weighted serial correlation of hedge fund returns as a proxy for illiquidity within the industry, Chan *et. al.*, (2005) find that there is a strong relationship between illiquidity in the hedge fund sector and shocks to global markets¹. When these systemic shocks occur, illiquidity in the hedge fund sector appears to rise dramatically. Chan *et. al.*, (2005) suggest that measures of liquidity exposures in the hedge fund industry can be a good measure of the degree of systemic risk.

Whilst the Chan *et. al.*, (2005) liquidity proxy for systemic risk is novel and innovative, it relies solely on hedge fund industry data. There are two issues associated with this definition of systemic risk.

¹ Serial correlation can also be interpreted as time-varying risk premia.

First, the hedge fund industry is just one of many important sectors of global financial markets. This information from the hedge fund industry may provide a partial measure of systemic risk within this sector of global financial markets, however, it is unlikely that such metrics can be employed to define systemic risk of the entire global financial system. Second, research by Fung and Hsieh (2000) and Liang (1999) have documented the reporting delays that are associated with hedge fund data, therefore, it is not practically feasible to employ the Chan *et. al.*, (2005) measure of systemic risk. While the contributions of Fung and Hsieh (2000) and Chan *et. al.*, (2005) are significant, the relationship between systemic risk and hedge fund returns remains a relatively unexplored area in the hedge fund literature.

As there is no single definition to describe systemic risk, the selection of a proxy for this metric is an important consideration. There is emerging evidence from the IMF (2009) and central bankers including Hildebrand (2007) that suggest that the TED spread is an efficient market proxy for global systemic risk. Studies such as Lashgari (2000) have revealed that the TED spread seems to fall during periods of high confidence, and rise during periods of low investor confidence. Changes in the TED spread also appear to be a source of equity volatility (see, Tse and Booth 1996). Lashgari (2000) finds that falling TED spreads are associated with rising equity markets, and vice versa. While this is indeed an interesting finding, the academic literature employing the TED spread is somewhat limited. Despite the lack of academic attention, practitioners and industry professionals have monitored the TED spread throughout the GFC as a barometer of global systemic risk. In order to examine the TED spread's significance, we test its effectiveness as an information variable against global hedge fund returns.

Given the dynamic shifts in systemic risk, it is important to consider how it interacts with hedge funds over time. The works of Fama and French (1989), Ferson and Harvey (1991) and Chen (1991) have demonstrated that key macroeconomic variables can explain the time-variation of equity returns. This raises the question of whether systemic risk can explain the variation of hedge fund returns as a risk factor and whether time-variation of hedge fund returns can be explained by systemic risk.

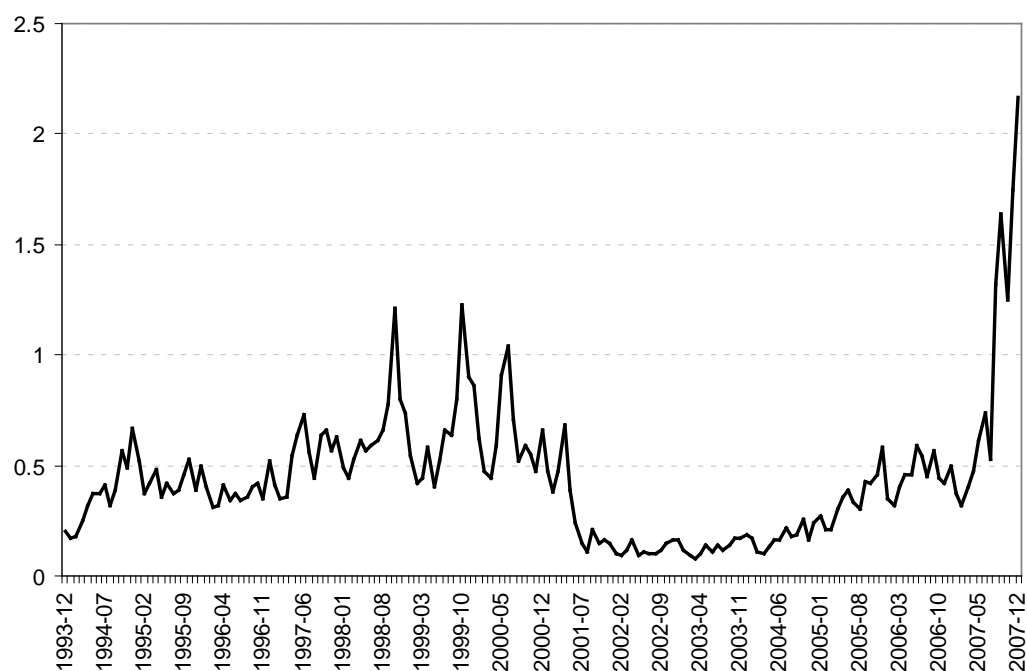
3. Data

This study employs data from January 1994 to December 2007 consisting of 168 monthly observations. This time period includes the Asian currency crisis of 1997, the Russian bond default crisis and the collapse of LTCM in 1998, the dot-com boom and bust from 1998-2000, 11th September 2001, and the commencement of the US subprime mortgage meltdown in 2007. The data section of this paper is divided into three parts. First, we describe the TED spread which is the proxy for systemic risk. The second section summarises the global hedge fund index returns employed in the study. Finally, the various independent variables in this study are considered.

The data for the construction of the TED spread is sourced from the United States Federal Reserve. The LIBOR rate is the 3 month yield on Eurodollars which banks charge each other for US deposits outside the regulatory framework of the US banking system.² Since these deposits are outside the jurisdiction of the Federal Reserve, they are deemed to be riskier.³ Investors therefore demand that they receive higher interest payments for accepting the lower liquidity and increased risk in Eurodollars. US Treasury bills on the other hand are regarded as one of the safest and most liquid investments in the world. Since Treasury bills are issued and backed by the USA government, there is a low to zero probability of default. It is well recognised that US Treasury Bills are highly liquid instruments that possess low risk and are often employed as the risk-free rate in finance studies. The yield difference between the premium on Eurodollars and Treasury bills is believed to capture the global credit risk premia, and is employed as a suitable proxy for systemic risk.

Figure 1: Treasury/Eurodollar (TED) Spread

This figure illustrates the yield difference between the 3 month LIBOR rate and the 3 month US Treasury Bill rate. Monthly yield data is employed from January 1994 to December 2007.



2 An example is an Australian resident depositing U.S dollars in an Australian bank.

3 Foreign banks holding Eurodollar deposits do not have to maintain reserve requirements to protect Eurodollar depositors. Furthermore, there is no deposit insurance for depositors, nor are central banks obligated to bail out Eurodollar depositors. This lower liquidity, coupled with the inflexibility for depositors to withdraw holdings as they please increases the risk of Eurodollar deposits.

Figure 1 illustrates the TED spread from January 1994 to December 2007. In this study, it is important to note that the changes in the TED spread are employed rather than the level of the TED spread which ensures stationarity in this independent variable. Figure 1 shows that rapid increase in the TED spread during the 1997 Asian crisis, the 1998 Russian and LTCM crisis and the more recent 2007 subprime US mortgage crisis. The TED spread also reveals period of low systemic risk from 2002 to 2004.

Table 1. Descriptive Statistics

This table reports the summary statistics of the data employed in this study. Panel A presents the monthly returns of the hedge fund index returns employed in this study. FOF=HFR Fund of Fund Index, CA=Convertible Arbitrage, DSB=Dedicated Short Bias, EM=Emerging Markets, EMN=Equity Market Neutral, ED=Event Driven, FIA=Fixed Income Arbitrage, GM=Global Macro, LSE=Long-Short Equity, and MF=Managed Futures. Panel B reports the monthly returns of the independent variables. Rm=US market value composite stock index, SMB=Fama-French Small-Minus-Big portfolio, HML=Fama-French High-Minus-Low Book to Market portfolio, UMD=Carhart 12 month momentum portfolio, WBIG= Citigroup World Broad Investment Grade (BIG) Bond Index, DJAIG=Dow Jones AIG Commodity Total Return Index, USDI=US Dollar Index, and MSCIXUS=MSCI World Equity Index excluding USA. Panel C presents the descriptive statistics of the basis point change in the TED spread. J-B Stat. and J-B p-val denotes the Jarque-Bera test statistic and p-value, respectively. * and ** denote statistical significance at the 5% and 1% levels, respectively.

Category	Mean	Std. Dev.	Skewness	Kurtosis	Median	Max.	Min	J-B Stat.	J-B p-val
<i>Panel A:</i>									
FOF	0.0065	0.0164	-0.2783	6.9657	0.0076	0.0685	-0.0747	112.26	0.001**
CA	0.0070	0.0133	-1.3569	6.2114	0.0102	0.0351	-0.0479	123.74	0.001**
DSB	-0.0015	0.0477	0.6285	4.1836	-0.0042	0.2047	-0.0909	20.87	0.003**
EM	0.0079	0.0456	-1.2115	10.0882	0.0148	0.1520	-0.2618	392.80	0.001**
EMN	0.0078	0.0081	0.3057	3.4329	0.0079	0.0321	-0.0116	3.93	0.101
ED	0.0093	0.0162	-3.625	29.7930	0.0105	0.0361	-0.1252	5392.98	0.001**
FIA	0.0051	0.0106	-3.0698	19.7535	0.0071	0.0203	-0.0721	2228.61	0.001**
GM	0.0108	0.0298	-0.2188	6.5757	0.0117	0.1008	-0.1227	90.84	0.001**
LSE	0.0096	0.0280	-0.0544	7.1682	0.0086	0.1223	-0.1214	121.70	0.001**
MF	0.0052	0.0343	-0.1078	3.2262	0.0034	0.0949	-0.0982	0.6834	0.500
<i>Panel B:</i>									
Rm	0.0062	0.0416	-0.7809	4.0773	0.0133	0.0818	-0.1620	25.20	0.002**
SMB	0.0013	0.0387	0.9069	10.5507	-0.0018	0.2218	-0.1670	422.12	0.001**
HML	0.0033	0.0349	0.0865	5.8981	0.0036	0.1380	-0.1280	59.00	0.001**
UMD	0.0094	0.5958	-0.6607	8.5896	0.0088	0.2208	-0.3006	230.93	0.001**
WBIG	0.0019	0.0145	0.0930	3.1224	0.0023	0.0458	-0.0369	0.35	0.500
DJAIG	0.0012	0.0375	-0.0621	2.6978	0.0009	0.0947	-0.0817	0.74	0.499
USDI	-0.0046	0.0208	-0.0281	2.9873	-0.0038	0.0498	-0.0558	0.02	0.498
MSCIXUS	0.0059	0.0419	-0.7238	3.9908	0.0094	0.0981	-0.1538	21.54	0.002**
<i>Panel C:</i>									
Δ TED Spread	0.0117	0.1467	1.0464	8.5875	0.0100	0.7900	-0.4100	249.21	0.001**

This second part of the data section describes the hedge fund returns employed in this study. We employ monthly index returns from Credit Suisse First Boston/Tremont to represent the returns of

the wide range of strategies employed in the global hedge fund industry. We use index returns instead of individual hedge fund returns so that we can measure the impact of the TED spread on the systematic returns of each hedge fund investment style. Amenc et al (2003) argue that the CSFB/Tremont hedge fund indices exhibit characteristics in index construction that offer substantial advantages over other competitors. The CSFB/Tremont indices only include funds that manage over certain amount of funds under management and provide audited financial statements. Approximately 300 funds are able to pass through this selection screen for inclusion in these indices. Furthermore, the CSFB/Tremont are the industry's only asset weighted hedge fund indexes. The allocation of funds to the indexes are recalculated quarterly and funds are not excluded from the database until they liquidate or fail to comply with reporting requirements. This index compliance requirements assists in minimising survivorship and backfilling bias in the database. To measure the overall returns from the global hedge fund industry, we also employ the HFR Fund of Funds Index. Fung and Hsieh (2000, 2002) have demonstrated that fund of funds (FOF) indexes exhibit the smallest levels of survivorship bias and backfilling bias and are therefore the most accurate measure of global hedge fund performance. The Ibbotson risk-free rate from the Kenneth French library is employed and continuously compounded returns are employed in the study.

Table 1 provides the descriptive statistics of the raw returns of the CSFB/Tremont indices and the HFR FOF Index. The statistics reveal the heterogeneous nature of the hedge fund universe with certain strategies exhibiting higher levels of volatility than others. The Dedicated Short Bias, Emerging Markets, Global Macro, Long-Short Equity and Managed Futures hedge fund indices exhibit higher levels of volatility in comparison to the other indices. In the sample period, Global Macro appears to exhibit the highest mean return.

Table 2 presents the correlation matrix of returns which further attests to the heterogeneous nature of the hedge fund universe. The highest level of correlation between the hedge fund indices is 0.85 between the HFR FOF Index and Long-Short Equity. This result is expected given that Long-Short Equity hedge funds represent a significant proportion of the global hedge fund industry.

Table 2. Correlation Matrix of Hedge Fund Returns

This table reports the correlation coefficients of the monthly returns of the hedge fund index returns. FOF=HFR Fund of Fund Index, CA=Convertible Arbitrage, DSB=Dedicated Short Bias, EM=Emerging Markets, EMN=Equity Market Neutral, ED=Event Driven, FIA=Fixed Income Arbitrage, GM=Global Macro, LSE=Long-Short Equity, and MF=Managed Futures.

Category	FOF	CA	DSB	EM	EMN	ED	FIA	GM	LSE	MF
FOF	1.000									
CA	0.504	1.000								
DSB	-0.626	-0.293	1.000							
EM	0.781	0.325	-0.545	1.000						
EMN	0.421	0.321	-0.346	0.251	1.000					
ED	0.803	0.579	-0.632	0.680	0.364	1.000				
FIA	0.446	0.536	-0.124	0.296	0.128	0.399	1.000			

GM	0.630	0.291	-0.151	0.425	0.213	0.379	0.440	1.000		
LSE	0.852	0.299	-0.727	0.606	0.353	0.670	0.227	0.434	1.000	
MF	0.117	-0.080	0.066	-0.040	0.150	-0.073	-0.005	0.258	0.056	1.000

This third part of the data section describes the independent variables employed as proxies for equity, bond, currency and commodity market returns and risk factors. The eight independent variables include the U.S. market weighted portfolio of all US stocks from the Kenneth French library, the Fama-French Small-Minus-Big (SMB) risk factor portfolio return, the Fama-French High-Minus-Low (HML) risk factor portfolio return, the Carhart (1997) Up-Minus-Down (UMD) 12 month momentum risk factor portfolio, the Citigroup World Broad Investment Grade (WBIG) Bond Index, the Dow Jones AIG Commodity Total Return Index, the U.S. Dollar Index and the MSCI World Equity Index excluding USA.

4. Methodology

The difficulty in modelling hedge fund performance has been the dynamic nature of hedge fund managers employing time-varying exposures to traditional asset classes. Managers tend to 'ride with the market' during bull market runs, and decrease their exposure during market downturns. This is one of the causes of the dynamic relationship between hedge fund returns and traditional asset classes that is often cited in the literature.

To examine the dynamic and time-varying nature of hedge fund exposures, we propose a conditional model of hedge fund performance. First, we employ the eight-factor unconditional model of Bianchi *et. al.*, (2008) and we then proceed to augment this unconditional model by conditioning it on changes in the TED spread. The TED spread will be employed as an information variable to examine whether changes in systemic risk can predict hedge fund returns. The motivation for this conditional model is to capture the time-varying behaviour of hedge fund returns when they shift their exposures in traditional asset classes based on changes in systemic risk. This is more acute as rising levels of systemic risk are often associated with downward movements in equity markets.

To model hedge fund returns, we employ the Bianchi *et. al.*, (2008) unconditional model as an alternative to the Capocci and Hubner (2004) or the Fung and Hsieh (2004) models. There are three rationales for the use of the Bianchi *et. al.*, (2008) framework. First, it has been found to readily capture the systematic returns of individual hedge funds and indexes. Second, the Bianchi *et. al.*, (2008) eight-factor model is more parsimonious than the Capocci and Hubner (2004) eleven-factor model. Third, the Bianchi *et. al.*, (2008) model avoids the use of lookback option returns as independent variables (IVs) as proposed in Fung and Hsieh (2004). Studies by Conze and Viswanathan (1991) and Parsons (1994) have shown that lookback options exhibit nonlinear return patterns due to their multiple path dependencies. The nonlinearity of returns from the lookback option payoffs make it very difficult and undesirable to assess the true statistical power of the standard errors of this IV in an OLS regression framework.

The Bianchi *et. al.*, (2008) unconditional eight-factor model is expressed as:

$$R_{i,t} - rf_t = \alpha_i + \beta_{1,i}(Rm_t - rf_t) + \beta_{2,i}HML_t + \beta_{3,i}SMB_t + \beta_{4,i}UMD_t + \beta_{5,i}(CITI_t - rf_t) + \beta_{6,i}(DJAIG_t - rf_t) + \beta_{7,i}(USDI_t - rf_t) + \beta_{8,i}(MSCIXUS_t - rf_t) + \varepsilon_{i,t} \quad (1)$$

where $R_{i,t}$ is the return on a hedge fund style at time t , Rm is the return on the U.S. market-weighted portfolio, rf is the risk-free rate, HML is the Fama-French factor-mimicking portfolio for book-to-market equity, SMB is the Fama-French factor-mimicking portfolio return for size, UMD is the Carhart (1997) factor-mimicking portfolio for 12 month momentum, $CITI$ is the return on the Citigroup World Broad Investment Grade Index, $DJAIG$ is the return on the Dow-Jones AIG commodity Total Return index, $USDI$ is the return on the U.S. Dollar index, $MSCIXUS$ is the return on the Morgan Stanley World Equity Index ex U.S. and ε is the error term.

The unconditional model in (1) is estimated via OLS with Newey and West (1987) corrected standard errors to account for possible heteroskedasticity and autocorrelation in the regression residuals.

The second model employed in this study is the same as (1) but has been conditioned to changes in the TED spread. The conditional model employed in this study is expressed as follows:

$$R_{i,t} - rf_t = \alpha_i + X'_t \beta_{1,i} + Z_{t-1} X'_t \beta_{2,i} + \varepsilon_{i,t} \quad (2)$$

where $R_{i,t}$ is the return on a hedge fund style at time t , rf_t is the risk-free rate, X'_t is a matrix of explanatory variables that include the eight factors in (1), and Z_{t-1} is the change in the TED spread at $t-1$, and ε_t is the error term.

$Z_{t-1} X'_t \beta_{2,i}$ measures the covariance between the betas in the model and the expected return based on the previous months change in the TED spread. It proxies as an interaction term between market factors and changes in the TED spread. $Z_{t-1} X'_t \beta_{2,i}$ provides a measure of the response of conditional betas to changes in the TED spread. If these coefficients are significant, it indicates that hedge fund managers exhibit time-varying exposure to asset class X based on the changes in the TED spread in the previous month, Z_{t-1} (see Ferson and Shadt (1996) and Ferson and Warther (1996)). If this is the case, then the TED spread may be employed to predict hedge fund returns. We now proceed to present the results of the analysis.

Table 3. Unconditional Model Estimates

This table presents the OLS estimates of the respective hedge fund index returns regressed against the unconditional eight-factor model. The table reports the regression coefficient estimates with the associated t-statistics in parentheses. FOF=HFR Fund of Fund Index, CA=Convertible Arbitrage, DSB=Dedicated Short Bias, EM=Emerging Markets, EMN=Equity Market Neutral, ED=Event Driven, FIA=Fixed Income Arbitrage, GM=Global Macro, LSE=Long-Short Equity, and MF=Managed Futures. Statistical significance was estimated with Newey and West (1987) corrected standard errors. * and ** denote statistical significance at the 5% and 1% levels, respectively.

	FOF	CA	DSB	EM	EMN	ED	FIA	GM	LSE	MF
A	0.0023** (2.8179)	0.0035* (2.3473)	0.0022 (0.9997)	0.0066* (2.0806)	0.0044** (5.5944)	0.0051** (4.6892)	0.0018** (1.9984)	0.0072** (3.1592)	0.0023 (1.9031)	0.0011 (0.4513)
$\beta(R_{m,t})$	0.0865* (2.3928)	0.0477 (1.3012)	-0.9157** (-11.0734)	-0.0640 (-0.4563)	0.0470 (1.7877)	0.1264** (3.3437)	-0.0155 (-0.3697)	0.1496 (1.3422)	0.4090** (7.9515)	-0.1514 (-0.9792)
$\beta(SMB_t)$	0.1458** (6.5491)	0.1114** (3.4819)	-0.2762** (-3.2845)	0.2214** (2.8293)	-0.0032 (-0.1997)	0.1389** (5.3535)	0.0549 (1.9160)	0.1101 (1.7885)	0.2078** (5.8861)	0.0108 (0.1359)
$\beta(HML_t)$	0.0265* (0.9514)	0.0998** (3.0146)	0.0719 (0.8467)	-0.0030 (-0.0329)	0.0077 (0.3606)	0.1211** (3.8070)	0.0556 (1.6669)	0.1176 (1.3688)	-0.0508 (-1.0337)	0.0649 (0.5894)
$\beta(UMD_t)$	0.0058** (4.4527)	-0.0009 (-0.6649)	-0.0020 (-0.4754)	0.0071* (2.0242)	-0.0005 (-0.5816)	0.0008 (0.6568)	0.0008 (0.5354)	0.0101* (2.2674)	0.0172** (6.8327)	0.0059 (1.6458)
$\beta(WBIG_t)$	0.2318** (3.6585)	0.1708* (2.1515)	-0.0706 (-0.4203)	0.4749* (2.2956)	0.0723 (1.2098)	0.1239* (2.0656)	0.2171* (2.3559)	0.9450** (4.2178)	0.2126* (2.4658)	0.4010 (1.2877)
$\beta(DJAI G_t)$	0.0533* (2.5862)	0.0075 (0.3072)	-0.0081 (-0.1294)	0.0741 (1.1232)	0.0191 (1.3663)	0.0250 (1.0943)	0.0215 (1.5279)	0.0593 (1.1034)	0.0489* (2.2170)	0.1766** (2.5262)
$\beta(USDI_t)$	0.2807** (5.9770)	0.1508 (0.3072)	-0.0345 (-0.3319)	0.8620** (4.2536)	0.0361 (0.8098)	0.1908** (2.7880)	0.1587 (1.6872)	0.7830** (4.0908)	0.0801 (1.3350)	-0.0799 (-0.3532)
$\beta(MSCIXUS_t)$	0.1844** (5.4203)	0.0316 (0.6015)	0.0266 (0.3515)	0.7470** (5.2950)	0.0247 (1.0186)	0.1603** (2.5552)	0.0555 (1.4144)	0.0941 (0.9944)	0.0693 (1.4507)	0.1095 (0.7211)
Adjusted R ²	0.6769	0.1115	0.7494	0.4902	0.1169	0.5353	0.0901	0.3095	0.8045	0.1015

Table 4. Conditional Model Estimates

This table presents the OLS estimates of the respective hedge fund index returns regressed against the eight-factor model conditioned on lagged changes in the TED spread. The table reports the regression coefficient estimates with the associated t-statistics in parentheses. FOF=HFR Fund of Fund Index, CA=Convertible Arbitrage, DSB=Dedicated Short Bias, EM=Emerging Markets, EMN=Equity Market Neutral, ED=Event Driven, FIA=Fixed Income Arbitrage, GM=Global Macro, LSE=Long-Short Equity, and MF=Managed Futures. Statistical significance was estimated with Newey and West (1987) corrected standard errors. * and ** denote statistical significance at the 5% and 1% levels, respectively.

	FOF	CA	DSB	EM	EMN	ED	FIA	GM	LSE	MF
α	0.0021* (2.2961)	0.0031* (2.0441)	0.0023 (1.0287)	0.0062 (1.8982)	0.0041** (5.2022)	0.0047** (3.8849)	0.0015 (1.7106)	0.0069** (3.2551)	0.0020 (1.5549)	0.0004 (0.1396)
$\beta(Rm_t)$	0.0777 (1.8234)	0.0440 (1.1155)	-0.9371** (-11.2005)	-0.0572 (-0.4000)	0.0452 (1.6356)	0.1255** (3.1322)	-0.0235 (-0.4641)	0.1250 (1.0363)	0.4038** (7.8867)	-0.1732 (-1.1054)
$\beta(SMB_t)$	0.1402** (4.9218)	.1100** (3.2142)	-0.2986** (-3.8850)	0.2131** (2.6838)	-0.0128 (-0.7245)	0.1301** (5.0764)	0.0498 (1.4551)	0.0988 (1.3809)	0.1903** (5.5740)	-0.0163 (-0.1920)
$\beta(HML_t)$	0.0301 (0.9050)	0.1084** (2.8394)	0.0572 (0.6453)	-0.0088 (-0.0925)	0.0070 (0.3169)	0.1229** (3.7624)	0.0679 (1.8579)	0.1340 (1.6047)	-0.0460 (-0.9759)	0.0694 (0.6077)
$\beta(UMD_t)$	0.0058** (3.9687)	-0.0014 (-0.9414)	-0.0010 (-0.2360)	0.0082* (2.2577)	-0.0002 (-0.2289)	0.0010 (0.8040)	0.0001 (0.0824)	0.0093** (2.7000)	0.0170** (7.5081)	0.0070 (1.8152)
$\beta(WBIG_t)$	0.2384** (3.1803)	0.1865* (2.1767)	-0.0946 (-0.5374)	0.4373 (1.9119)	0.0548 (0.9505)	0.1177 (1.8304)	0.2231* (2.1390)	1.0028** (4.0942)	0.2364** (2.6435)	0.3750 (1.1711)
$\beta(DJAI G_t)$	0.0558** (3.2918)	0.0049 (0.1974)	-0.0055 (-0.0856)	0.0770 (1.1363)	0.0257 (1.9405)	0.0293 (1.1472)	0.0292 (1.8148)	0.0571 (1.1129)	0.0588* (2.1740)	0.1993* (2.5768)
$\beta(USDI_t)$	0.2849** (3.9918)	0.1548 (1.5294)	-0.0620 (-0.5729)	0.8428** (3.8657)	0.0154 (0.3448)	0.1850* (2.5715)	0.1541 (1.5080)	0.8395** (3.913)	0.0965 (1.4851)	-0.1042 (-0.4506)
$\beta(MSCIXUS_t)$	0.1965** (4.1975)	0.0292 (0.5540)	0.0627 (0.9155)	0.7492** (5.1289)	0.0251 (1.0248)	0.1636* (2.5087)	0.0565 (1.3435)	0.1424 (1.4269)	0.0815 (1.7161)	0.1383 (0.9191)
$\beta(Rm_t)(Z_{t-1})$	0.0975 (0.5566)	-0.3136 (-1.3313)	1.5559* (2.3310)	0.8895 (1.1696)	0.1975 (0.9998)	0.1607 (0.7708)	-0.0840 (-0.3198)	-0.0319 (-0.0664)	-0.2298 (-0.9012)	1.1027 (1.4908)
$\beta(SMB_t)(Z_{t-1})$	0.0396 (0.2665)	0.1062 (0.7048)	-0.2482 (-0.5050)	0.1614 (0.4061)	0.1416 (1.5116)	0.0719 (0.4945)	0.2220 (1.3671)	-0.5093 (-1.7820)	-0.1934 (-1.1009)	0.5658 (1.3111)

$\beta(\text{HML}_t)(Z_{t-1})$	-0.0821 (-0.3755)	-0.1593 (-0.8580)	0.1568 (0.2059)	-0.0273 (-0.0502)	-0.0393 (-0.3074)	-0.0966 (-0.4843)	0.2616 (1.4661)	-0.5941 (-1.4508)	-0.0672 (-0.1802)	0.4228 (0.8067)
$\beta(\text{UMD}_t)(Z_{t-1})$	-0.0131* (-2.2485)	-0.0104 (-1.4157)	-0.0027 (-0.1543)	-0.0123 (-0.5691)	-0.0092 (-1.8380)	-0.0142* (-2.5188)	-0.0028 (-0.4898)	-0.0360 (-2.5086)	-0.0227** (-3.1389)	-0.0365* (-2.0014)
$\beta(\text{WBIG}_t)(Z_{t-1})$	0.8205 (1.5131)	1.7136** (2.7265)	-0.0422 (-0.0306)	0.1845 (0.1097)	1.0043** (2.7380)	0.8676 (1.7698)	1.9158* (2.4142)	1.2609 (0.9215)	0.3035 (0.4857)	2.4540 (1.3918)
$\beta(\text{DJAIG}_t)(Z_{t-1})$	0.2204* (2.4801)	0.0404 (0.3910)	-0.0848 (-0.3087)	0.0741 (0.2267)	-0.0238 (-0.3148)	0.1056 (0.9642)	0.1169 (0.8908)	1.0425** (3.9952)	0.2130 (1.6325)	0.3947 (1.3678)
$\beta(\text{USD}_t)(Z_{t-1})$	0.3935 (1.2017)	0.3936 (1.0007)	-0.3272 (-0.5107)	-0.4269 (-0.3541)	0.3691 (1.2673)	0.2793 (0.9297)	0.8874 (1.9268)	1.1992 (1.1390)	0.6679 (1.7743)	0.9713 (0.9265)
$\beta(\text{MSCIXUS}_t)(Z_{t-1})$	-0.2397 (-1.2908)	0.2864 (1.7369)	-1.6823** (-3.4160)	-0.7124 (-0.8133)	-0.0871 (-0.4513)	-0.1043 (-0.4638)	0.2596 (1.4882)	-0.7266 (-1.4278)	0.2595 (1.0817)	-0.9451 (-1.5275)
Adjusted R ²	0.6758	0.1169	0.7540	0.4685	0.1270	0.5233	0.1108	0.3498	0.8119	0.0850

5. Results

The results section of the paper is divided in two parts. First, we present the regression results of the unconditional eight-factor model in (1). These results provide an understanding of the market returns and risk factors that are explanatory variables of various hedge fund returns and investment styles. Second, we report on the regression results of the eight-factor conditional model in (2) when conditioned to changes in the TED spread.

(i) Unconditional Model

Table 3 presents the regression results of the hedge fund index returns against the unconditional eight-factor model from (1). The results in Table 3 reveal that the simple eight-factor model is relatively successful at identifying the market exposure of hedge funds to traditional asset classes. The HFR Fund of Funds (FOF) Index is regarded as the overall measure of the global hedge fund industry and reports an R^2 of 0.6769 with positive and statistically significant factor loadings for all eight factors. These results are consistent with Capocci and Hubner (2004) and Fung and Hsieh (2002) who suggest that the overall returns of the global hedge fund industry can be explained by conventional market returns and risk factors.

The performance of the Fixed Income Arbitrage model reports the poorest result with an R^2 of 0.0901, however, the high R^2 's in the Long-Short Equity (0.8045) and Dedicated Short Bias (0.7494) models reveal that these hedge fund index returns are derived from conventional market factors. Another striking feature of Table 3 is that each hedge fund index return exhibits different statistical significant factor loadings for the eight-factor model. The results in Table 3 demonstrate the heterogeneous nature of the hedge fund universe, as various hedge fund strategies are exposed to different market factors. However, the statistical significance of all factor loadings for the Fund of Funds (FOF) index indicates that the industry as a whole bears significant exposure to conventional market factors.

(ii) Conditional Model

In this section, the independent variables employed in the eight-factor model in Eq. (1) are conditioned to the changes in the monthly TED spread. Statistically significant conditioning variables will suggest that hedge fund managers employ dynamic exposures to market risk factors in response to changes in systemic risk, and thus, systemic risk may be used as a predictor of hedge fund returns. In the conditional model in (2), it is the sign of the statistically significant conditional variable that is important, rather than the actual factor loading. Since the market factors are conditioned on the TED spread, a positive coefficient indicates that a hedge fund style is increasing its exposure to that particular market factor as the TED spread widens. On the other hand, if the conditional variable is negative, it means that as the TED spread widens (narrows), the hedge fund style is decreasing (increasing) its exposure to a particular market factor. The significance of a conditional variable

implies that hedge fund managers are exhibiting time-varying exposures to a certain market factor, which results in changing betas through time.

Table 4 presents the hedge fund index returns regressed against the eight-factor model with the TED spread conditioning information variable as detailed in (2). An examination of the factor loadings with the TED spread information variable reveal the following general discoveries. At first glance, we can see that the TED spread provides statistically significant information for every hedge fund index except Emerging Markets. First, all significant UMD conditional factor loadings are negative which reveals that as the TED spread (systemic risk) increases or widens, hedge funds reduce their systematic exposure to the momentum risk factor. Second, the significant WBIG and DJAIG conditional factor loadings are positive in Table 4 which reveals that as the TED spread increases (systemic risk rises), hedge funds increase their systematic exposure to world bonds and commodities. The results in Table 4 demonstrate that the TED spread provides important information content on the general behaviour of hedge funds and how their exposures change with fluctuations in systemic risk.

A closer examination of each hedge fund index group in Table 4 reveals the following observations. The HFR FOF index exhibits statistically significant time-varying exposures to the momentum risk factor (-0.0131) and commodity returns (0.2204). These significant interaction coefficients for the HFR FOF index demonstrates that the global hedge fund industry reduces their time-varying exposures to the momentum risk factor and increases their exposure to commodities in response to increasing levels of systemic risk as measured by the TED spread.

Another striking result from Table 4 is the behaviour of the Dedicated Short Bias (DSB) hedge fund index returns. The unconditional factor loading for US equity returns in Table 3 is -0.9371, however, Table 4 reports a significant interaction coefficient of 1.5559. These two coefficients which imply that DSB funds increase their short US stock beta market factor as the TED spread widens. Put simply, short sellers increase their short exposures in the US as systemic risk increases. This finding is economically rational for short sellers as rising systemic risk usually results in falling stock markets (see, Lashgari 2000).

The behaviour of Fixed Income Arbitrage (FIA) reveals a significant unconditional factor loading for world investment grade bonds (WBIG) returns of 0.2231 in Table 3 with a significant interaction coefficient of 1.9158 reported in Table 4. These results imply that FIA funds increase their long exposure to investment grade bond returns with increases in the TED spread. This behaviour represents a type of 'flight to quality' purchasing of investment grade bonds during times of rising systemic risk.

Overall, the conditional regression R^2 s in Table 4 do not significantly improve the unconditional regression R^2 s in Table 3. The findings in Table 4 reveal that the TED spread as a conditioning variable does not improve the explanatory power of unconditional eight-factor model, however, it is clear that the TED spread provides important information content on the dynamic behaviour of hedge fund exposures in conventional markets and risk factors. It is also important to acknowledge that Table 4 provides evidence that hedge fund index returns reflect compensation for the time-variation of conventional market factors, however, the statistically significant intercept terms suggest that systemic risk as an information variable is not the sole conditioning factor that can explain hedge fund returns.

6. Conclusion

This study examines the fluctuations of the TED spread and considers whether this surrogate measure of systemic risk explains the time-variation of hedge fund returns. When employed as a conditioning variable in a multifactor model, the TED spread reveals new information on the behaviour of hedge fund returns. First, we reveal that increases in the TED spread results in hedge fund managers decreasing their exposure to the momentum risk factor. The TED spread also reveals that short sellers increase their short exposure when confronted with rising systemic risk. As shown in Lashgari (2000), rising levels of systemic risk are generally associated with rapidly falling stock markets and the TED spread in this study reveals the opportunistic behaviour of short sellers under these types of market conditions. We also discover that as the TED spread widens, it is shown that Convertible Arbitrage, Equity Market Neutral and Fixed Income Arbitrage hedge funds increase their exposures to world investment grade bonds.

This study contributes to the hedge fund literature in finding that a proxy for systemic risk such as the TED spread can predict dynamic shifts in market related exposures by hedge funds. A small limitation of the TED spread is that it appears to be insignificant at predicting changes in exposures to other investment markets such as currencies, world equities, value and small stocks. Another limitation of the conditional regression model is that it does not seem to increase the explanatory power of the unconditional model.

The study introduces the TED spread to the hedge fund literature as a new explanatory variable which assists us in understanding the behaviour of global hedge fund returns. The TED spread demonstrates that rising systemic risk results in changes in exposure to US equities and global bond markets in the global hedge fund industry. An avenue for future research is the examination of the TED spread in predicting bull/bear markets or the volatility of hedge fund returns. Another potential area of future research is whether hedge funds adjust their portfolio positions based on expected states of the economy which is captured by the TED spread. We leave these interesting considerations for future research.

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