SYRTO

SYstemic Risk TOmography
Signals, Measurements, Transmission Channels, and Policy Interventions

Sovereign and Hedge Fund Systemic Risk Nexus

Enrico Ciavolino, Roberto Savona

SYRTO WORKING PAPER SERIES
Working paper n. 18 | 2015

This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement n° 320270.

Sovereign and Hedge Fund Systemic Risk Nexus

by

Enrico Ciavolino (University of Salento) and Roberto Savona (University of Brescia)

The common view about the role played by the hedge funds during the global financial crisis of 2007-2009 is that they threaten the financial system. Recently, the Wall Street Journal[1] emphasized the point by referencing to Gropp (2009) who stated, “More important than commercial banks or investment banks, hedge funds may be the most important transmitters of shocks during crises”. New evidence seems confirms this view, as proven by Adams, et al. (2013) who show that more than banks and other financial intermediaries, hedge funds act as primary source of adverse shocks to the other financial institutions. While there is large consensus on how strong is the interconnectedness degree of hedge funds within the financial system (see Billio et al., 2012), a tangential yet less explored issue regards the connection between sovereign risk and hedge funds. The question became relevant especially during the recent Eurozone sovereign debt crisis. Indeed, the global financial crisis erupted in 2007, which achieved systemic dimension in 2008 with the Lehman crash, forced governments to save their domestic banking systems from collapse, and problems in the banking sector spilled over to sovereign balance sheets. As a result, in 2010-2011 many Euro countries experienced huge sovereign spread increases driven in large part by negative market sentiments, more than underlying macroeconomic fundamentals (De Grawe and Ji, 2013).

As important players of the financial markets, looking for absolute returns through complex investment strategies, hedge funds may have contributed significantly with such an excess surge in sovereign spreads. In fact, when arbitrage opportunity are exploitable, and market prices are distant to their fundamentals, these sophisticated investors intervene with the objective to maximize their profits riding or feeding bubbles and anti-bubbles trends in the market.

[1] Al Lewis, “The Systemic Risk of Hedge Funds”, The Wall Street Journal, April 19, 2014.

This paper aims at inspecting the role and the contribution of hedge funds in the sovereign risk in the Eurozone. To such an extent, we introduce novel systemic risk measures for (a) Eurozone core countries (France and Germany), (b) GIIPS (Greece, Ireland, Italy, Portugal and Spain), and (c) hedge fund industry. The systemic risk measures we introduce are latent variables (similar to Principal Components) conditional on some observable covariates. Technically, we extract latent variables from financial asset returns (sovereign CDS and hedge fund indices) while using some observable covariates (VIX, EU and US term spread, ted spread) we assume they act as "main causes" of systemic risk. Using data on sovereign CDS for France, Germany, Greece, Ireland, Italy, Portugal, Spain, and hedge fund indices over the period from January 2008 to August 2013, our results provide new evidence about the connection between hedge funds and sovereign risk in the Eurozone. Hedge fund sector contributed significantly with the rise of systemic risk for GIIPS and "core" countries during the Greek crisis of 2010 and the Eurozone crisis of 2011. From July 2012 hedge funds explained more than half of GIIPS risk variations (reaching 0.7 as explained variance on a 12 months rolling regression), while for core countries the contribution became substantial (more than 0.5 as explained variance) starting from 2013. The risk factor loading computed using the hedge fund systemic risk factor as explanatory variable shown positive values until the end of 2010, which became negative up to August 2013. We ascribe this finding to the different risk exposition assumed by hedge funds, which moved from long to short position on sovereign risk.

We proceed as follows. We first focus on sovereign and hedge fund risks. Then we present our novel methodology proposed to come up with systemic risk measures conditional on some observable covariates. We next present our empirical findings on sovereign and hedge fund systemic risks, and we comment on our main findings about the relationship between sovereign and hedge fund systemic risks. Finally, we report our conclusions.

SOVEREIGN RISK

We measure the sovereign risks in the Eurozone using the 5 years US dollar denominated sovereign CDS for France and Germany (Core) together with Greece, Ireland, Italy, Portugal, Spain (GIIPS). As well known, sovereign CDS are like insurance contracts used to protect investors against losses on sovereign debt. Hence, the premiums paid for obtaining default protection reflect the market price of sovereign credit risk. As noted by Longstaff, et al. (2011), the important advantage of using sovereign CDS is that these contracts are typically more liquid than the corresponding sovereign bonds, thereby offering more accurate market-based sovereign risk estimates. Data on sovereign CDS comes from Bloomberg and relate to end-to-month quotes over the period from December 2007 to August 2013.

Sovereign CDS are explored based on a simple pricing model using country-specific macro- and financial-variables. Based on the abundant literature on sovereign CDS pricing (e.g., see Augustin, 2014), sovereign CDS are econometrically explained by following variables: (1) Debt over GDP; (2) exports over GDP; (3) GDP growth rates; (4) industrial production; (5) inflation rate; (6) unemployment rate; (7) domestic stock index. Data comes from Thompson Reuters Datastream and refer to end-to-month level over the same period from December 2007 to August 2013. For each of the 7 sovereigns in our sample, we regress the monthly returns in the CDS on the first-difference of the 7 country-specific explanatory variables described above using the following equation:

$$CDS_{j,t} = \alpha_j + \sum_{v=1}^{7} \beta_{j,v} M_{j,t} + \upsilon_{j,t}, \tag{1}$$

where $CDS_{j,t}$ is the monthly return computed using the end-of-month spread levels for country *j* at time *t*. α_j is a constant for country *j*, $\beta_{j,v}$ is the sensitivity towards variable $M_{j,t}$ of country *j*, and $\upsilon_{j,t}$ is the residual of CDS at time *t*.

HEDGE FUNDS RISK

Hedge fund risk is explored using the Credit Suisse First Boston/Tremont (CSFB Tremont) Indices. These are asset-weighted hedge fund indices computed for ten style categories accounting for at least 85% of the AUM in each group. To inspect the risk dynamics of hedge funds we use the risk factor model proposed by Fung and Hsieh (2001, 2004, 2007a,b), which includes both linear and option-like factors. Specifically, we include the following hedge fund factors:

- Two equity-oriented risk factors: (1) Equity Market Factor, proxied by the Standard & Poors 500 index monthly total return (SP) and (2) Size Spread Factor (SIZE), proxied by Wilshire Small Cap 1750 minus Wilshire Large Cap 750 monthly returns.
- Two bond-oriented risk factors: (1) Bond Market Factor, proxied by the month end-to-month end change in the 10-year treasury constant maturity yield (C10YR) and (2) Credit Spread Factor (CS), proxied by the month end-to-month end change in the Moody's Baa yield less the 10-year treasury constant maturity yield.
- Five primitive trend-following strategies proxied as pairs of standard straddles and constructed from exchange-traded put and call options, namely (1) Equity Trend-Following Factor (PTFSSTK); (2) Bond Trend-Following Factor (PTFSBD), (3) Interest Rate Trend-Following Factor (PTFSIR) (4) Currency Trend-Following Factor (PTFSFX) and (5) Commodity Trend-Following Factor (PTFSCOM)[2].

Based on the above factors, hedge fund strategies are econometrically specified through the following equation:

(2) $$r_{HFi,t} = a_{HFi} + \sum_{k=1}^{9} B_{HFi,k} F_{k,t} + e_{HFi,t} \, .$$

[2] The above factors slightly differ from the "original" model which includes an Emerging Market index and does not use the equity and the interest trend-following factors. Not reported in the paper, but available upon request, our preliminary results contrasting our factor selection with the original model, shown better diagnostics with our 9 factors for all the 10 hedge fund indices in terms of adjusted R squared, and number of significant estimated coefficients.

$r_{HFi,t}$ is the return of the hedge fund index *i* for time *t*, a_{HFi} is the intercept (Jensen's alpha), $B_{HFi,k}$ is the factor loading of hedge fund index *i* on factor *k*, $F_{k,t}$ is the return of factor *k* for month *t* and $e_{HFi,t}$ is the error term.

SYSTEMIC RISK(S)

As pointed out by Billio et al. (2011), the heart of systemic risk is the commonality among multiple institutions. Therefore, Principal Components Analysis (PCA) is a reasonable methodology to come up with an effective systemic risk indicator. And indeed, many recent papers documented significant commonality in financial markets using PCA. Longstaff et al. (2011) find that first principal component extracted from the changes in sovereign CDS spreads of 26 developed and less-developed countries explains 64 percent of the total variation occurred during the period 2000-2010. Billio et al. (2012) captures the 77% of variability among financial institutions (hedge funds, brokers, banks, and insurers) over the period 1994-2000, which increases to 83% in 2001-2008. Kritzman et al. (2011) introduce an implied measure of systemic risk computed as the fraction of the variance of a set of asset returns explained by a fixed number of eigenvectors (absorption ratio) computed using global stocks, bond, real estate and commodities. In our paper, we propose a novel approach to estimate systemic risk, conceived as a latent variable conditional on a specified set of common covariates. Computationally, we rely on the Partial Least Squares (PLS) estimation method within a Multiple Indicators Multiple Causes (MIMIC) modeling framework (see below). According to the MIMIC representation, we assume that:

- A first latent variable affects the CDS variations of France and Germany and represents the sovereign systemic risk for Core countries in the Eurozone;
- A second latent variable affects the CDS variations for GIIPS and represents the sovereign systemic risk of "peripheral" countries in the Eurozone;
- Finally, a third latent variable affects the hedge fund index variations and represents the hedge fund systemic risk.

The three systemic risk measures are all linked to the same set of covariates we assume they cause the dynamics of the three latent variables (systemic risks).

The partial least squares-path modelling (PLS-PM) for the MIMIC can be thought as two conceptually different models: (1) a *measurement model* that specifies the relationships between the multiple indicators $\mathbf{y}$ with the latent variable ξ; (2) a *structural model* that specifies the relationship between the latent variable ξ and their relative multiple causes $\mathbf{x}$. Mathematically,

(3)

(4)

where Eq. (3) is the measurement model, while Eq. (4) is the structural model. $\mathbf{y}$ is the vector of the multiple indicators; is the vector of the (one single sector-specific) systemic risk; is the loading matrix of sensitivities towards the systemic risk ξ; is the path matrix of sensitivities towards the common covariates $\mathbf{x}$; finally, $\boldsymbol{\varepsilon}$ and $\boldsymbol{\tau}$ are, respectively, the vectors of measurement and structural errors.

The estimation of the parameters and follows a double approximation as compromise between measurement and structural model, that means external and internal estimation (Ciavolino et al. 2013). Per each block j of latent variable, the *external estimation* $\mathbf{v}_j$ is obtained as product between the block of manifest variables and *outer weights* $\mathbf{w}_j$, while, the *internal estimation* $\mathbf{z}_j$ is obtained as the product between of the external estimation of $\boldsymbol{\xi}_j$, $\mathbf{v}_j$, and the *inner weights* $e_{j,i}$.

The PLS algorithm starts by initializing outer weights (generally they are fixed to one for the first MV of each LV and zero for all the remaining ones); then, the parameter estimation is performed, until convergence, by iteratively computing

1. *external estimation*, $\mathbf{v}_j = \mathbf{X}_j \, \mathbf{w}_j$;

2. *internal estimation*, ; and

3. *outer weight estimation*, with Mode A or Mode B (see Ciavolino 2012).

The causal paths among LVs (the coefficients in the matrix) are obtained through the ordinary least squares (OLS) method or PLS regression.

The graphical (MIMIC-based) representation of the two sub-models is reported in Figure 1, which depicts the conceptual framework of systemic risk, assumed as the latent variable that maximally explain, in a causal relationship sense, the dynamics of which in turns is caused by multiple common covariates .

Model Estimation

The concept of systemic risk is by its own nature antithetic to risk idiosyncrasies, being the risk imposed by interlinkages and interdependencies within the financial sector as a whole. For that reason, in our empirical analysis we used the residuals of Eqs. (1) and (2), thereby focusing on the so-called "filtered returns" of CDS and hedge funds. This is because with all likelihood systemic risk sits on commonalities among unexplained returns. As well known, it is indeed during systemic shocks that we observe extreme and unexpected return variations, which occur with increased commonality.

Specifically, we proceed as follows:

- First, we estimate Eq. (1) for the 7 CDS (Core and GIIPS) and the 10 hedge fund indices, using the country-specific covariates for the sovereign risk and the 9-factors model for hedge fund risk as discussed above.
- Second, once obtained regression estimates in the previous step, we next compute the corresponding error terms for each regression. These are the multiple indicators which enters into the MIMIC representation (see Figure 1) as . More precisely, we use: (a) 2 indicators for core countries , (b) 5 indicators for GIIPS , and (d) 10 indicators for hedge funds . *T* denotes the time horizon from January 2008 to August 2013.
- Third, we estimate the sector-specific systemic risk measures for each group (CORE, GIIPS, hedge funds) by running Eqs. (3-4). , , are the multiple indicators for the

corresponding , , , and the entering into the MIMIC scheme (again, see Figure 1) are the observable covariates we selected as the main common causes of the three "latent-based" systemic risks. In more depth, by referring upon the main literature on systemic risk, country risk, and hedge fund risk, the following 4 covariates were selected: (1) VIX index; (2) US and (3) Euro Term Spread, computed as the difference between the ten-year and two-year government bond yields of the corresponding geographical areas; (4) TED spread, calculated as the difference between the three-month LIBOR and the US 3-Month T-bill rate.

RESULTS

Sovereign Systemic Risks

Table 1 reports the structural model estimates (Eq. 4) for Core (Panel A) and GIIPS (Panel B), respectively. Two are the major findings arising from the analysis: First, the model explains a good explanatory power for the dynamics of Core sovereign systemic risk, denoting an R square of 0.337, while the explanatory power for GIIPS is 0.171. Second, by exploring the contributions of single covariates we note that, for CORE, the significance is reached for Euro Term Spread and TED Spread, while VIX index and TED Spread are the significant covariates for GIIPS. As we may expect, the dynamics of systemic risk for Core and GIIPS are quite different both in terms model stability, and risk drivers. Indeed, one the one hand (Core) the linear relationship between the latent systemic risk and the 4 covariates seems sufficiently robust, and the path coefficients show expected sign, since higher TED Spread values are with increasing funding risk and steepened Euro Term Spread is almost attributable to a rise in investor aversion to long-term fixed income. On the other hand (GIIPS), the explanatory power is low, and an (at first sight) anomalous negative value is reported for TED Spread. To explore the point in more depth we run model estimates through bootstrap technique. The results are in Table 2 for Core (Panel A) and GIIPS (Panel B).

In order to assess the significance of the path coefficients and R square, confidence intervals are computed by bootstrapping 200 random samples. Based on such estimates we then conclude that the

GIIPS systemic risk exhibited a time-varying relationship in which the 4 covariates sometimes really matters, while in others they did not at all, especially during turbulence periods such as the Lehman collapse of 2008. The negative sign for TED Spread could be due both to a time-varying sensitivity with the covariate and a sort of risk pricing convergence between Core and GIIPS. In more depth, a rise in Core cds spreads connected to upturns in funding risk variation may signal a general sovereign risk re-pricing whereby, overpriced GIIPS are relatively corrected downwards when instead Core risk show a relatively upward correction.

Instead, bootstrap estimates for Core are virtually the same as compared to the PLS estimation run over the entire sample, thereby indicating a time-homogeneous relationship over the inspected interval.

Hedge Fund Systemic Risk

Table 3 reports results from the structural model estimation for hedge fund indices. As for sovereign systemic risks, we run the procedure also checking the robustness by computing bootstrap estimates, which are reported in Panel B. The numbers reported in Table 3 show a lower explanatory power of the model, while covariates appear significant for Euro Term Spread (with a p-value of 0.0607) and near-to-be-significant for US Term Spread (the p-value is 0.1005) and TED Spread (the p-value is 0.1039). Bootstrap estimates indicate a great time-dependent relationship between the latent variable and the 4 covariates, as the R square moves from 0.086 to 0.221. The result is interesting as it proves good explanatory power on average (0.221 is indeed the arithmetic average computed over all the bootstrapped samples). The negative coefficient for VIX Index indicates a net volatility seller tendency assumed by hedge funds as a whole, while the negative coefficient of US Term Spread is in line with Savona (2014) who finds negative coefficient of term spread for many hedge fund indices, suggesting that funds could be engaged in a possible "sell-short and buy-long" scheme, namely funds selling short and buying long-term bonds. Differently, the coefficient for Euro Term Spread is positive, in this case suggesting a reversed "sell-short and buy-long" scheme in which the funds finance their investments in Euro bonds by selling long-term Euro bonds. Finally, the positive coefficient for TED Spread seems to confirm the liquidity timing ability of hedge funds recently proven in Cao et al. (2013), as the TED Spread represents the funding liquidity risk factor.

Systemic Risk Nexus

Having extracted systemic risk measures for Core, GIIPS, and hedge funds, we now inspect the two-way connections between sovereign and hedge fund systemic risks. As discussed in the introduction, the point is relevant especially in light of the surge in the sovereign cds exhibited during the 2010-2011 by the peripheral Euro countries. To what extent hedge funds contributed to the dynamics of sovereign systemic risks? How did they do, namely what positions hedge funds assumed? Since our systemic risk measures are based on filtered returns, it is plausible that even a simple rolling regression with which sovereign risks are regressed against hedge fund systemic risk could give us some insights about the two above questions. We then computed 12-months rolling regression using the following expression:

(5) $$\xi_{Z,t} = \alpha_Z + \beta_Z \cdot \xi_{\mathrm{HF},t} + \tau_{Z,t}$$

with $Z = \mathrm{CORE}, \mathrm{GIIPS}$. We focus on both the explained variance by the hedge fund systemic risk computed as $\left[(\beta_Z)^2 \cdot var(\xi_{\mathrm{HF}})\right] / var(\xi_Z)$, thereby assessing the role played by the hedge fund in the sovereign systemic risk dynamics, and on the time variability of the β_Z, thus shedding some light on the positions assumed by the hedge funds relative to GIIPS and Core dynamics.

Figure 2 reports the time-varying explained variance for Core and GIIPS over the period December 2008 – August 2013. Based on these results, we note that hedge fund sector played a significant role with the rise of systemic risk for both Core and GIIPS during the Greek crisis of 2010 and the Eurozone crisis of 2011. A first peak of the explained variance is indeed localized during the first half of the 2010, namely with the explosion of the Greek crisis, with values of about 0.45 for Core, and 0.34 for GIIPS. A second peak is during 2011 with values for both Core and GIIPS around 0.3. From July 2012 hedge funds explained more than half of GIIPS risk variations, reaching 0.7, while for Core countries the contribution became substantial starting from 2013 with values higher than 0.5.

In Figure 3 we report rolling betas of Eq. (5). Interestingly, until the end of 2010 the values for Core and GIIPS are positive, while from January 2011 to the end of the inspected period the values are negative, except for Core over the sub-period November 2011 – October 2012 where the values move around zero. Since the systemic risks for Core, GIIPS and hedge funds are based on (filtered) returns, positive betas denote positive hedge fund returns associated with increases in CDS spreads, while negative betas denote negative performance for hedge fund industry when sovereign systemic risks tend to increase. As a result, we may conjecture that over the first period, when betas were positive for Core and GIIPS, hedge funds assumed long positions towards sovereign systemic risks, making profits with increases in sovereign CDS spreads. Over the second period, when betas moved to negative values, it is instead plausible that hedge funds changed their positions from long to short, thereby achieving positive returns with downtrends in sovereign risk dynamics. Such a change was definitely the case for GIIPS, while for Core, as commented before, during the sub-period November 2011 – October 2012 the coefficients assumed on average values around zero, thus suggesting more investigation on the point. To that end, we computed the time-varying beta of the hedge fund systemic risk against Core and GIIPS systemic risks running a 12-month rolling regression as in Eq. (5), but using as dependent variable $\xi_{\mathrm{HF},t}$ and as covariate $\xi_{Z,t}$. The results are shown in Figure 4, which confirms our conjecture about the position assumed by hedge fund industry as a whole towards Core and GIIPS. Indeed, up to the end of 2010, betas relative to Core and GIIPS moved in tandem and were positive, while during the period January 2011 – August 2013 betas moved differently. Namely, betas against Core were positive reaching a peak in August 2012 (the value is 0.553), when instead betas against GIIPS were negative with a downward peak in July 2012 (the value is −1.377). Afterwards, and specifically from April 2013, the betas converged moving around −0.5 up to August 2013. Therefore, during the sub-period November 2011 – March 2013, it seems that hedge funds were long on Core and short on GIIPS, as if they betted on marginal increases in Core spreads together with downwards adjustments to the GIIPS risk, while the general tendency over the second period was short on average both towards Core and GIIPS.

CONCLUSIONS

Sovereign risk and hedge funds became an important issue to explore especially during the recent Eurozone sovereign debt crisis, when governments, banks and other financial intermediaries fueled a systemic risk difficult to understand, in terms of its dynamics, and complex to explain, in terms of sector contributions and connected risk drivers. In this paper we focus on the relation between sovereign systemic risk and hedge fund systemic risk also inspecting their single dynamics and connected main causes. We find that VIX, term spread and TED spread are able to explain a substantial part of the dynamics of systemic risks, for both sovereign and hedge fund sectors. We also find that hedge fund sector contributed significantly with the rise of systemic risk for GIIPS and core countries in the Eurozone. On average, hedge funds assumed long positions, in a first period (from December 2008 to March 2011), and short positions, in a second period (from April 2011 to August 2013), relative to sovereign CDS of GIIPS as well as of France and Germany.

References

Adams, Zeno, Roland Füss, and Reint Gropp. 2013. "Spillover Effects among Financial Institutions: A State Dependent Sensitivity Value at Risk Approach (SDSVar)." Forthcoming, Journal of Financial and Quantitative Analysis.

Charles Cao, Yong Chen, Bing Liang, Andrew W. Lo (2013) Can hedge funds time market liquidity?. Journal of Financial Economics 109 (2013) 493–516.

Ciavolino, E. (2012). General distress as second order latent variable estimated through PLS-PM approach. *Electronic Journal Of Applied Statistical Analysis, 5*(3), 458-464.

Ciavolino, E., & Nitti, M. (2013). Using the Hybrid Two-Step estimation approach for the identification of second-order latent variable models. *Journal of Applied Statistics*, *40*(3), 508-526.

De Grauwe, P., Y. Ji (2013). Self-fulfilling crises in the Eurozone: An empirical test," Journal of International Money and Finance, Volume 34, April 2013, Pages 15–36.

Augustin P. (2014), Sovereign Credit Default Swap Premia, Journal of Investment Management, 12(2):65-102.

Longstaff, Francis A., Jun Pan, Lasse H. Pedersen, and Kenneth J. Singleton. 2011. "How Sovereign Is Sovereign Credit Risk?" American Economic Journal: Macroeconomics, 3(2): 75-103.

Monica Billio, Mila Getmansky, Andrew W. Lo, Loriana Pelizzon (2012) "Econometric measures of connectedness and systemic risk in the finance and insurance sectors" Journal of Financial Economics Volume 104, Issue 3, June 2012, Pages 535–559.

Kritzman, M., Y. Li, S. Page, and R. Rigobon, 2010, "Principal Components as a Measure of Systemic Risk," The Journal of Portfolio Management Summer 2011, Vol. 37, No. 4: pp. 112-126 .

Savona R. (2014). Risk and Beta Anatomy in the Hedge Fund Industry. European Journal of Finance 20 (1), 1-32.

Table 1: PLS Estimates

	coefficient	***p*-value**
Panel A: Core Countries		
VIX	0.023	0.845
US Term Spread	0.002	0.987
Euro Term Spread	0.411	0.004
TED Spread	0.376	0.002
R square	0.337	
Panel B: GIIPS		
VIX	0.303	0.025
US Term Spread	0.197	0.204
Euro Term Spread	0.108	0.490
TED Spread	-0.233	0.078
R square	0.171	

Table 2: Bootstrap Estimates

	coefficient	**0.025**	**0.975**
Panel A: Core Countries			
VIX	0.017	-0.218	0.278
US Term Spread	0.003	-0.265	0.266
Euro Term Spread	0.379	-0.006	0.683
TED Spread	0.318	-0.141	0.575
R square	0.358	0.039	0.707
Panel B: GIIPS			
VIX	0.275	-0.056	0.502
US Term Spread	0.174	-0.177	0.450
Euro Term Spread	0.103	-0.295	0.496
TED Spread	-0.228	-0.535	0.239
R square	0.265	0.08	0.465

Table 3: Hedge Fund Estimates

	coefficient	*p*-value	0.025	0.975
Panel A: PLS Estimates				
VIX	-0.076	0.583	-	-
US Term Spread	-0.269	0.101	-	-
Euro Term Spread	0.311	0.061	-	-
TED Spread	0.226	0.104	-	-
R square	0.086		-	-
Panel B: Bootstrap Estimates				
VIX	0.082	-	-0.339	0.405
US Term Spread	0.406	-	-0.506	0.336
Euro Term Spread	0.283	-	-0.584	0.545
TED Spread	0.169	-	-0.470	0.501
R square	0.221	-	0.049	0.523

Figure 1: MIMIC

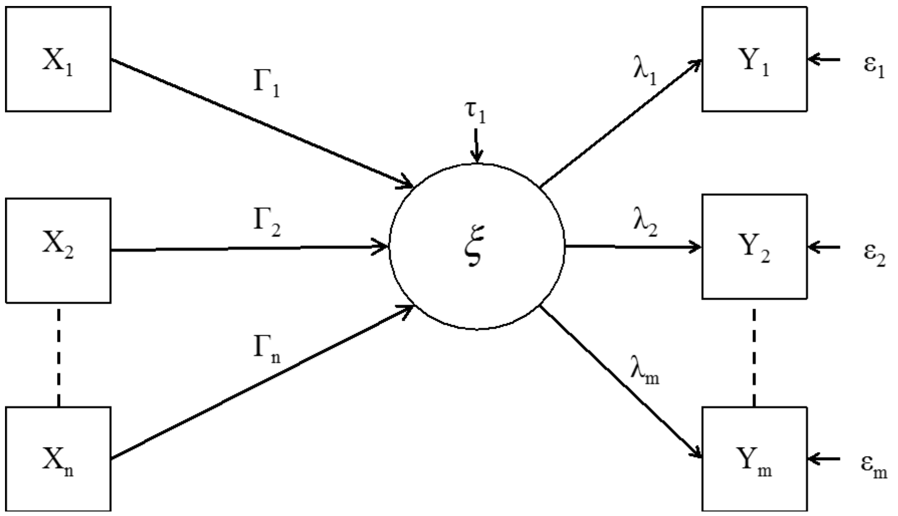

Figure 2: Explained Variance

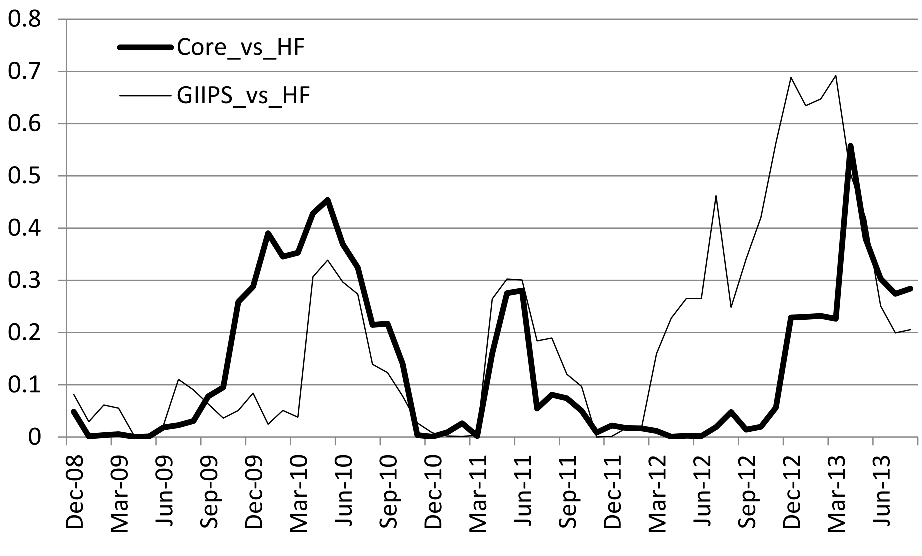

Figure 3: 12-month Rolling Betas

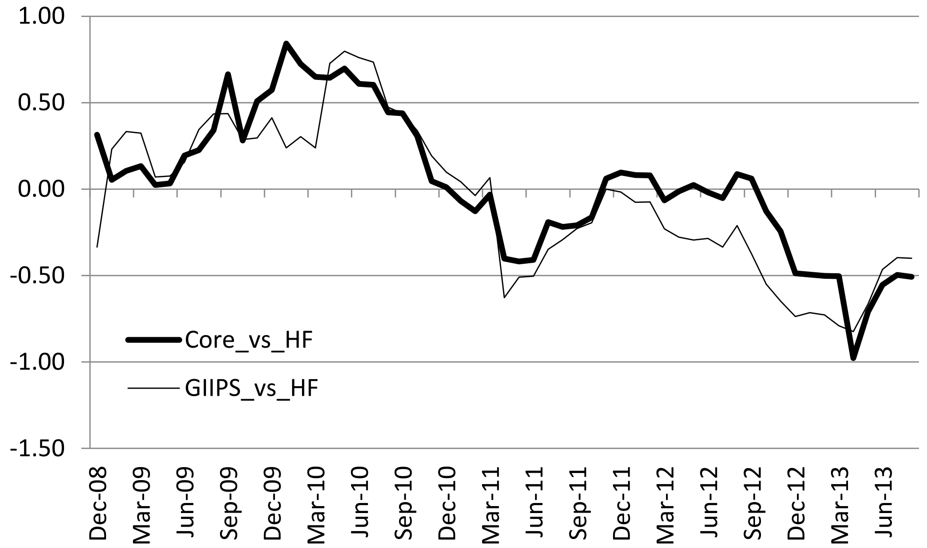

Figure 4: 12-month Rolling Beta