A systemic risk indicator and monetary policy

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This version: 21 April 2012. Preliminary version. Please do not quote.

Abstract

We propose a comprehensive indicator able to measure systemic risk at a global level. The indicator is constructed by integrating the dynamics of international financial and commodity markets with signals emerging from the economic cycle. Based upon 1995-2011 crisis events, we show the capability of the proposed indicator to interpret recent financial history. We also test the interaction of the indicator with monetary policy decisions employed by the FED and the ECB. There is evidence that expansionary decisions adopted by the FED were led by riskiness of the system, while the ECB showed some reluctance to give up its role in maintaining price stability, except during the recent period of economic and financial instability.

Keywords: Systemic risk, financial instability, monetary policy, structural breaks, Autometrics.

JEL classification: C13, C22

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†We wish to thank participants in the 9th OxMetrics User Conference (London, 16-17 September, 2010), in particular Sir David F. Hendry and Neil R. Ericsson, in the seminar at the Board of Governors of the Federal Reserve System (Washington, 14 March 2012), in particular Lamont K. Black, Celso Brunetti and Grayham Mizon, in the Third International Conference in Memory of Carlo Giannini (Bank of Italy, 12-13 April 2012), in particular Wanda Cornacchia and Hashem Pesaran, in the EMG-ESRC Workshop on Global Linkages and Financial Crises (Cass Business School, 27 April 2012) in particular Marco Lo Duca, for useful discussions and valuable comments. We are indebted to Matteo Mogliani and Christian de Peretti for technical support and for helpful discussions. The usual disclaimer applies. Riccardo Pianeti acknowledges financial support from the Centre of Econometric Analysis.

1. Introduction

This paper has two main objectives. First, we propose a comprehensive indicator able to measure systemic risk at a global level; second, we focus our analysis on the interaction of the indicator with policy decisions employed by the FED and the ECB during the crisis.

Measuring systemic risk. The 2007-2009 crisis originated in the market of mortgage-backed-securities and spread rapidly across the credit market and then to the overall capital market with a severe impact on the solidity of the international banking system. The effects of the crisis on the real economy are still to be fully understood. The current European sovereign debt crisis is just the last of a series of systemic events whose market depth and persistence have questioned the much celebrated markets' self-regulatory power as well as the overall ability of policy makers and regulators to adopt overall stability measures and stimulate economic growth.

Just as in 2007-09, the current financial crisis demonstrates that systemic risk spreads globally across markets and institutions. Funding difficulties in one market/country can spill over to other markets/countries via internationally active institutions, and the tail risk in financial markets can be transmitted across the world.

There are several methodological approaches to measure systemic risk. A first line of research focuses on the international banking system, the systemic event is induced by severe disequilibria within the banking sector: Lehar (2005), Adrian and Brunnermeier (2011), and Zambrana (2010) adopt standard risk management techniques to assess banks' credit risk exposure and capital deficits resulting into a systemic crisis; Martınez-Jaramillo et al. (2010) and Billio et al. (2010) focus on the interbank market to analyze disequilibria with a potential systemic effect; Bartram et al. (2007) benchmark three different methods to quantify the risk of a systemic failure in the global banking system; Huang et al. (2009) measures systemic risk by estimating the cost of insuring a hypothetical portfolio containing debt instruments issued by the 12 major U.S banks; Huang et al. (2011) extend the previous work to 19 large US bank holding companies again within a structural credit risk framework based on correlated financial and economic variables (such as FED Funds Rates, market returns and volatility); Giglio (2011) focuses on the financial sector including American as well as European financial institutions now relying on bond prices as well as credit default swaps explicitly measuring the market assessment of those institutions' default likelihood.

Another stream of contributions focuses on global (rather than limited to the financial sector) market dynamics as primary source of financial instability. In this case, market information needs to be framed within a more general methodological approach. The international banking sector remains central to the analysis, but global banks' weakness may not be sufficient to induce a systemic event.

The Global Systemic Indicator proposed by Sullivan et al. (2010) considers 5 markets (US equity, non-US equity, fixed income, high yield and real estate) and defines a systemic event as the simultaneous fall of the returns of (at least) 3 markets, below their 5^{th} percentile. Their systemic risk indicator is given by the probability of the systemic event to occur, as generated by a logistic model. Interestingly, the authors map into a binary risk indicator dynamics generated in the option market (through the VIX Index), the credit market (through the AAA spread over the 10 year Treasury rate) and money market (through the spread between T-bill and Eurodollar futures rates). However, the resulting indicator appears difficult to be interpreted and highly volatile. In addition, the authors analyze key relations between a set of financial variables but the analysis is limited to the US financial market thus ignoring the real side of the economy. The joint treatment of financial markets' and economic cycle's information to assess systemic risk appears a requirement for policy makers and global institutions: the 2007-2009 crisis, just as more recent events, shows the limits of risk models for the financial crisis neglecting the economic cycle. Indeed the pro-cyclicality of international capital standards has been called upon (Allen and Saunders, 2003) to explain the crisis' depth. The link with the real economy is paramount to assess systemic risk, and thus in our paper we propose a systemic risk indicator which includes macroeconomic variables able to capture the overall (financial and economic system) impact of systemic risk. In the same spirit is the paper by De Nicolò and Lucchetta (2011) who propose a modeling framework leading to distinct forecasts for a financial and a real systemic indicator. Also inspired by the G10 systemic risk definition, the authors propose a real measure of systemic risk such as the GDP-at-risk defined as "the worst predicted realization of quarterly growth in real GDP at 5% probability", while a financial risk measure is proposed through the financial system-at-risk (FSaR), defined as "the 5% worst predicted realization of market-adjusted returns for a large portfolio". Though inspired by the same systemic risk definition, rather than proposing two separate indicators, in our paper we propose a global measure of systemic risk.

A comprehensive approach to systemic risk assessment is also proposed by Schwaab et al. (2011) who adopt a dynamic state-space model to determine forward crises indicators with underlying macro-financial and credit risk variables. Here macroeconomic variables are introduced to explain the time dynamics of expected default frequencies in US and Europe. The information structure is very rich and the authors propose a financial distress indicator based on early warning signals, thus also partially forward looking. More importantly, the authors focus on joint global economic and financial movements to qualify the systemic assessment and translate such information into a risk indicator defined in the $[0, 1]$ set, thus interpretable as a probability measure. Similarly in our paper, an extended information basis is maintained, capturing systemic events at an international level and a risk indicator with similar statistical properties is derived. The definition of systemic risk adopted by Schwaab et al. (2011) is based on a simultaneous failure of a large number of financial intermediaries, and the estimation procedure identifies multiple systemic risk indicators, directly referred to the financial sector only. On the contrary, the indicator we propose is more comprehensive as it can be considered a global risk factor.

Monetary policy decisions adopted by the FED and the ECB during the crisis. The other main aim that inspired our work in proposing a global risk indicator is the possibility to evaluate the reactions of monetary policy makers during crises. Building a leading indicator able to guide monetary policy in preventing systemic instability is very timely (Trichet, 2009). The definition of a global risk indicator allows us to test, through an extension of the Taylor rule (Taylor, 1993), the relationship between systemic risk and monetary interventions by the Federal Reserve and the European Central Bank since 1995 and 1999 respectively. We follow up from an early work by Hayford and Malliaris (2005), who investigated the reaction of the FED to the late '90 stock market bubble by extending the Taylor rule to include a measure of overvaluation of the American stock market. Gnan and Cuaresma (2008) provide an estimate for the 4 major Central Banks (the ECB, the FED, the Bank of Japan and the Bank of England) of the Taylor Rule augmented by a financial instability variable, namely the equity return volatility for each of the area considered. The empirical estimates allow authors to conclude for the presence of relevant differences in the elasticity of interest rates to financial instability. In our paper, we aim to understand how Central Bankers react to a shift in the riskiness of the system and to this purpose we extend the relation proposed in Gnan and Cuaresma (2008) by including the proposed systemic risk indicator as well as by considering in the sample the period of the recent financial crisis. Thus, the application developed in this study adds to previous works the analysis of monetary responses to a common systemic risk threat, being the indicator constructed from international data.

The main findings in this paper can be summarized as follows. Based upon the 1995-2011 crisis events, the global systemic risk indicator we propose is able to interpret the recent financial history. Further, the empirical investigation on the interaction of the indicator with monetary policy shows that expansionary decisions adopted by the FED in recent years were also led by riskiness of the system. On the contrary, there is evidence that ECB showed some reluctance to give up its role in maintaining price stability, except during the recent period of economic and financial instability.

The remainder of the paper is organized as follows. In Section 2., we describe the methodology behind the construction of the systemic risk indicator, and we report an empirical application to show the capability of the proposed indicator to capture the crisis events over the period 1995-2011. Section 3. reports an empirical investigation on the interaction of the indicator with monetary policy decisions employed by the FED and the ECB during the crisis. Section 4. concludes.

2. Systemic risk indicator

In this section, we introduce the risk indicator able to provide a quarterly measure of the global riskiness in the economic and financial system. First, the indicator can be regarded as a mapping from a set of exogenous economic and financial variables to a risk measure in the $(0, 1)$ space, with 0 indicating absence of systemic risk and 1 maximum systemic risk. The indicator is calibrated to exploit the rich history of events observed over the period 1995-2011. By introducing a filtered average systemic risk fluctuation, time-varying positive and negative deviations from such average are considered and monetary interventions are related to those deviations. A logistic model is adopted to link this indicator to a set of explanatory variables selected on the basis of the definition of systemic risk provided by the official documentation of the G10 Report on Consolidation in the Financial Sector (G10, 2001, p.126):

Definition 1 ***(Systemic Financial Risk)*** *Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy.*

The proposed indicator is based on wide coverage of the data in respect of different asset classes and geographical areas considered, with data referred to daily quotes for a wide definition of the financial system including equity, fixed income and commodity markets (for details see Section 2.3.). To measure the economic loss that may occur in financial markets, a *risk appetite index* is constructed following the methodology used by Credit Swiss First Boston (CSFB) as described in Wilmot et al. (2004). There is a stream of the literature that shows that risk appetite measures have a very high ability in explaining financial market movements, including systemic instabilities (Kumar and Persaud, 2002; Bandopadhyaya and Jones, 2006). Extending the market coverage, market instability is related to a homogeneous fall of financial market risk premiums, which denotes a relevant outflow of financial resources from the markets. Taking this view, low systemic risk is characterized by the presence of positive risk premiums and diversification among markets, with inflows and outflows from a market to another. As for the measure of the uncertainty in financial markets, the *average discrepancy of the volatilities from their long-term value* is considered to capture positive and negative deviations from long-term benchmark. Such approach is also consistent with the risk appetite methodology. The risk indicator is an increasing function of positive deviations from the market-specific long-term volatility. Finally, in order to keep track of the real economy conditions of the system (adverse effects on the real economy), the *output gap* of a set of countries is considered, so that a wide geographic area is covered.

From a methodological viewpoint, the introduction of several time-varying gap measures for financial markets' dynamics and the economic cycle allows the definition of a systemic risk indicator with cyclical features. Such property allows an endogenous and normalized characterization of systemic risk relevant for economic agents and policy makers alike. As a robustness check of our conclusions on the relationship between monetary policy and systemic risk, several alternative models are tested, taking into account the presence of structural breaks, which is tested following Doornik (2009) and Castle et al. (2011).

Let $\xi \in (0,1)$ denote the systemic risk, where $\xi \to 0^+$ indicates vanishing systemic risk, while $\xi \to 1^-$ corresponds to systemic risk approaching its maximum. The indicator is defined as a logistic transform:

$$\xi \equiv \left[1 + \exp\left(-\beta_0 - \beta_1 \sum_{k=1}^{K} \gamma_k \tilde{X}_{\cdot,k}\right)\right]^{-1} \tag{1}$$

where $\tilde{X} \in \mathbb{R}^{T \times K}$ is the normalized version of the matrix $X \in \mathbb{R}^{T \times K}$ of explanatory variables, such that:

$$\tilde{X} \equiv \left\{\tilde{X}_{t,k} \middle| \mathbb{E}\left(\tilde{X}_{t,k}\right) = 0, \mathbb{E}\left(\tilde{X}_{t,k}\right)^2 = 1, \forall k\right\} \tag{2}$$

where $t = 1, ..., T$ is the sample period and $k = 1, ..., K$ the number of the explanatory variables. The coefficient vectors $\beta \equiv [\beta_0 \ \beta_1]'$ and $\gamma \equiv [\gamma_1 \ldots \gamma_K]'$ have to be estimated.

There are two main issues to cover, namely the choice of the variables in X and the estimation procedure to get estimates of β and γ.

2.1. The choice of the relevant variables

In this section, we provide a description of the variables in X as defined in (1). Our presentation develops as if the data set used is at quarterly frequency.

Let us first focus on *risk appetite index*. Suppose we have $i = 1, ..., I$ markets for a certain number of quarters $t = 1, \ldots, T$ and a benchmark index for each of them. Let $\mu_{i,t}$ and $\sigma_{i,t}$ be the average and the standard deviation of the returns for index i during quarter t, respectively. Then, for each quarter, the following regression is estimated:

$$\mu_{i,t} = c_t + \alpha_t \sigma_{i,t} + \varepsilon_{i,t} \tag{3}$$

where by construction we set $c_t = 0$. The slope α_t and the determination coefficient R_t^2 of the regression above are inputs to the systemic risk index.

Following (3), increasing systemic risk over time is captured by a decreasing and negative estimate for α_t, corresponding to negative risk premiums and an outflow of financial resources from the markets at time t. The higher R_t^2, the stronger the markets' investments outflow. On the other hand, a situation of low systemic risk is characterized by the presence of positive risk premiums and diversification among markets, with inflows and outflows. This situation is likely to correspond to a positive estimate of α_t and a very low R_t^2. Hence, the systemic risk indicator is a *decreasing* function of α_t and an *increasing* function of R_t^2.

To measure *the uncertainty in financial markets,* let us define the average percent deviation of the volatilities from their long-term value σ_i^{LT}:

$$s_t \equiv \frac{1}{I} \sum_{i=1}^{I} \frac{\sigma_{i,t} - \sigma_i^{LT}}{\sigma_i^{LT}} \tag{4}$$

where σ_i^{LT} with $i = 1, \ldots, I$ are the full-sample standard deviations of the returns on the i-th index. The systemic risk indicator is an *increasing* function of s_t, as increasing volatilities over their long term values are directly associated with financial instability.

In order to monitor the real economy conditions of the system, the time series of the output gap is considered for several countries, covering a wide geographic area. The output gap $y_{\cdot,j}$ for country j with $j = 1, \ldots, J$ is estimated as the percentage logarithmic deviation of the actual GDP from the potential GDP:

$$y_{t,j} \equiv 100(g_{t,j} - g^*_{t,j}) \tag{5}$$

where $g_{t,j}$ is the logarithm of the actual GDP for the j-th country, while $g^*_{t,j}$ is the logarithm of the potential GDP. The potential GDP is computed applying a univariate Hodrick-Prescott (1997, HP henceforth) filter to the logarithm of the original series of the GDP with smoothing parameter λ_{HP} set to 1600, consistent with the relevant literature on this topic, as for instance in Ravn and Uhlig (2002). This method is less accurate than the production function approach (Arnold, 2004), but it is less costly from a computational point of view and it is still reliable for our purposes. The systemic risk indicator is expected to be a *decreasing* function of $y_{\cdot,j}$ with $j = 1, \ldots, J$.

To summarize, the relevant variables in the matrix X and the expected sign of the relation between each of them and ξ is:

$$X \equiv \begin{bmatrix} \underset{(-)}{\alpha} & \underset{(+)}{R^2} & \underset{(+)}{s} & \underset{(-)}{y_{\cdot,1}} & \dots & \underset{(-)}{y_{\cdot,J}} \end{bmatrix} \tag{6}$$

2.2. Parameters estimation

Once that the variables of interest are identified, the systemic risk indicator (1) can be obtained if we have an estimation of the vector parameters β and γ. In (1), we first get γ, estimated via discriminant analysis, then β is derived.

We discriminate between high and low systemic risk regimes within the sample, by identifying explanatory variables' extreme observations and then splitting them into two subsets, one for high systemic risk conditions and the other for low risk. Let $v \in \mathbb{R}^K$ be a threshold vector defined by:

$$v \equiv \begin{bmatrix} 0 & \bar{R}^2 & \bar{s} & 0 & \dots & 0 \end{bmatrix}' \tag{7}$$

where $\bar{R}^2$ and $\bar{s}$ are the 50-th constant percentiles of R_t^2 and s_t respectively. A natural choice of the threshold for α_t and $y_{t,j}$ is 0, having these variables an immediate financial and economic interpretation. Now, let τ^+ and τ^- identify the extreme high and low systemic risk observation sets, defined as:

$$\tau^+ \equiv \{t | X_{t,k} > v_k, \forall k\} \text{ and } \tau^- \equiv \{t | X_{t,k} < v_k, \forall k\} \tag{8}$$

leading to the subsets of normalized explanatory variables:

$$\tilde{X}^+ \equiv \left\{ \tilde{X}_{t,\cdot} | t \in \tau^+ \right\} \text{ and } \tilde{X}^- \equiv \left\{ \tilde{X}_{t,\cdot} | t \in \tau^- \right\}. \tag{9}$$

In a multidimensional space, the normalized positive deviations from the mean is achieved by introducing the sets centroids of the sets $\tilde{X}^+$ and $\tilde{X}^-$:

$$_c\tilde{X}_k^+ \equiv \frac{1}{|\tau^+|} \sum_{t \in \tau_+} \tilde{X}_{t,k} \text{ and } {}_c\tilde{X}_k^- \equiv \frac{1}{|\tau^-|} \sum_{t \in \tau_-} \tilde{X}_{t,k} \tag{10}$$

with ${}_c\tilde{X}^{+'}$ and ${}_c\tilde{X}^{-'}$ being column vectors, elements of $\mathbb{R}^K$. $\gamma \in \mathbb{R}^K$ is estimated by solving the following optimization problem:

$$\begin{aligned} \min_{\gamma \in \mathbb{R}^K} \quad & \left[\sum_{t \in \tau^+} \left| {}_c\tilde{X}^+\gamma - \tilde{X}_{t,\cdot}\gamma \right| + \sum_{t \in \tau^-} \left| {}_c\tilde{X}^-\gamma - \tilde{X}_{t,\cdot}\gamma \right| \right] \\ \text{s.t.} \quad & \underline{1}'\gamma = 1 \\ & \gamma_k \geq \bar{\gamma}_k \quad \forall k = 1, \ldots, K \end{aligned} \tag{11}$$

where $\bar{\gamma}_k$ is a lower bound on γ_k. Problem (11) can be rewritten as a linear programming problem by introducing a set of auxiliary variables, one for each observation in the sets τ^+ and τ^-:

$$\begin{aligned} \min_{\gamma \in \mathbb{R}^K} \quad & \left[\sum_{t \in \tau^+} z_t^+ + \sum_{t \in \tau^-} z_t^- \right] \\ \text{s.t.} \quad & \underline{1}'\gamma = 1 \\ & -z_t^+ < {}_c\tilde{X}^+\gamma - \tilde{X}_{t,\cdot}\gamma < z_t^+ \quad \forall t \in \tau^+ \\ & -z_t^- < {}_c\tilde{X}^-\gamma - \tilde{X}_{t,\cdot}\gamma < z_t^- \quad \forall t \in \tau^- \\ & \gamma_k \geq \bar{\gamma}_k \quad \forall k = 1, \ldots, K \\ & z_t^+ \geq 0 \quad \forall t \in \tau^+ \\ & z_t^- \geq 0 \quad \forall t \in \tau^- \end{aligned} \tag{12}$$

The implementation of this procedure provides us with $\hat{\gamma}$, an estimate of γ.

The estimates of β_0 and β_1 are derived as follows. Let $\tilde{X}_{\hat{\gamma}}^-$ and $\tilde{X}_{\hat{\gamma}}^+$ be two representative percentiles of the linear combination $\tilde{X}\hat{\gamma}$, say the $100p^+$-th and the $100p^-$-th percentiles. A natural choice for p^+ and p^- is:

$$p^- \equiv \frac{|\tau^-|/T}{2} \tag{13}$$

$$p^+ \equiv 1 - \frac{|\tau^+|/T}{2} \tag{14}$$

Then the estimates of β_0 and β_1 are obtained by solving the following system of equations:

$$\begin{cases} \xi\left(\beta|\tilde{X}_{\hat{\gamma}}^-\right) = p^- \\ \xi\left(\beta|\tilde{X}_{\hat{\gamma}}^+\right) = p^+ \end{cases} \tag{15}$$

which can be linearized as:

$$\begin{cases} \beta_0 + \beta_1 \tilde{X}^{-}_{\hat{\gamma}} = -\ln\left[(p^{-})^{-1} - 1\right] \\ \beta_0 + \beta_1 \tilde{X}^{+}_{\hat{\gamma}} = -\ln\left[(p^{+})^{-1} - 1\right] \end{cases} \tag{16}$$

Since $\tilde{X}^{-}_{\hat{\gamma}} \neq \tilde{X}^{+}_{\hat{\gamma}}$ by construction, the system has always a unique solution $\hat{\beta}$.

We have now $\tilde{X}$, $\hat{\gamma}$ and $\hat{\beta}$, and thus the in-sample time series for ξ can be constructed according to (1).

The procedure has several interesting features. Firstly, it is based on the probability space partition of the historical distribution of the explanatory variables. As such, the assessment accuracy of the systemic risk indicator increases with time. Secondly, a high systemic risk measure can only be achieved if financial and commodity markets are jointly falling, the average historic volatility is high and the economic cycle of the major world economic areas is negative. Any deviation from the worst case percentiles of either underlying variables decreases the value of the risk indicator. Thirdly, financial instability phenomena originating within the financial sector and thus resulting into heavy market losses of financial securities impacts the overall systemic risk assessment only if they determine broader market turmoil and an economic downturn. Fourthly, high and low systemic risk conditions are discriminated with respect to endogenous time-varying average values which lead to a mean-reverting behavior of the relevant explanatory variables and the risk indicator. Finally, no causality effect is considered *a-priori* from financial markets into the real economy, nor vice-versa.

2.3. Evaluating the capability of the indicator to capture the crisis events over 1995-2011

In this section, we describe the procedure to estimate the indicator proposed above using 17 years of data spanning from 1995:1 to 2011:4 ($T = 68$). The systemic risk indicator is estimated using daily quotes of 21 benchmark indices for the following asset classes: equity, bond, corporate, money market and commodity, covering the following geographical areas: United States, Euro Area, United Kingdom, Japan, Emerging Countries. Furthermore, the

GDP of these geographical areas is considered. Details about these two data-sets are reported in Tabs. 1 and 2.

[Tabs. 1-2 about here]

The estimates for α, R^2 and s are plotted in Fig. 1, while the normalized output gap indices are reported in Fig. 2.

[Figs. 1-2 about here]

In Fig. 1, one can see α (top panel of the figure) falls during instability periods of the recent financial history, such as the Asian Crisis, the period around September 2001 and the 2007-2009 economic and financial downturn. It is worth noticing that for the last two cases a peaking R^2 can be also observed, witnessing a homogeneous outflow from financial markets. s has a remarkable peak between end 2008 and before 2009, revealing that in that period, in a context of high degree of uncertainty, the volatilities in financial markets were on average 50% higher than the historical ones.

Fig. 2 shows the high correlation between the economic cycles especially during 2008. One can clearly notice the jump of the Japanese economy just before the Asian Crisis and the expansionary trace followed by the United States in the late '90s.

In order to estimate the parameters according to the methodology in Section 2.2., the observations integrating our definition of τ^+ and τ^- have to be found. Not surprisingly the observations in τ^+ are: 2008:4, 2009:1 and 2009:2, while those in τ^- are: 2006:3, 2006:4 and 2007:4. The period between 2008 and 2009 can be thought as the most relevant in terms of systemic risk out of the previous 15 years.

The second half of 2006 has been detected as a period of very low systemic risk: that period was characterized by a positive macroeconomic *status* as well as by the presence of a positive risk premium in the markets. In the last quarter of the 2007, the first effects of the subprime crisis hit the North American market inducing, still in a positive macroeconomic context, an outflow towards fixed income securities. The subprime crisis was at the time a US phenomenon, not yet affecting the overall system and the systemic risk indicator.

The derivation of the systemic risk indicator requires as inputs the estimated β and γ coefficients. The linear programming in (12) is first solved, setting the lower bounds for the parameters as follows:

$$\bar{\gamma} \equiv \frac{1}{2}\begin{bmatrix}\frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{6} & \frac{1}{18} & \frac{1}{18} & \frac{1}{18}\end{bmatrix}' \tag{17}$$

This choice corresponds to the case of one half of a even weighting of the variables, in which the lower bounds on the coefficients referred to the UK, Japan and Emerging Market cyclical indicators are constrained to be one third of the Euro Area and US coefficients.

By solving the linear programming in (12) and the linear system in (16), we get the estimates:

$$\hat{\gamma} = [.478 \quad .083 \quad .189 \quad .083 \quad .083 \quad .028 \quad .028 \quad .028]' \tag{18}$$

$$\hat{\beta} = [-1.415 \quad 2.637]' \tag{19}$$

The solution of the optimization problem to estimate γ assigns a higher weight to financial variables, and in particular to α and s, to allow the indicator to embody different systemic risk scenarios (see also Fig. 1). Fig. 3 reports the systemic risk indicator that we obtain.

[Fig. 3 about here]

Alternative specifications of the bounds, $\bar{\gamma}$, are also considered. In particular, we also re-estimated the model by specifying either $\bar{\gamma} = \underline{0}$ or, without imposing any bounds, $\bar{\gamma}_k = -\infty, \forall k$. For both cases, the predominance of the financial variables, especially of α and s, is preserved; however, the estimates of the parameters for the cyclical indicators show some degree of variability mainly due to the high collinearity of the cyclical indicators, as can be seen in Fig. 2. The robustness check showed that the systemic risk indicator is not affected by the alternative bounds adopted, just as unaffected are the dates corresponding to τ^+ and τ^-.

2.4. A dynamic equilibrium value and the recent financial history

Given the estimated systemic risk indicator ξ_t, we want to determine a smooth and time-varying *fundamental* equilibrium value for it. This allows us to discriminate between positive and negative deviations of the time-t estimate ξ_t from its long-term trend, which will be denoted as ξ_t^*, being an input to the empirical analysis of the monetary response to systemic risk.

Consider the following exponential weighted moving average with decay factor λ:

$$\xi_t^* \equiv \ddot{\xi}_t^* + \lambda^{T-t+1}(\bar{\xi}^* - \ddot{\xi}_t^*) \tag{20}$$

where $\ddot{\xi}_t^*$ is the trend component of the systemic risk indicator time series, detected using the HP filter (with smoothing parameter set equal to 1600), while $\bar{\xi}^*$ is defined as the value of ξ_t conditional on $X_{t,\cdot} = \tilde{v}$, the normalized threshold vector v. λ is chosen in the interval $[0, 1]$ so that $\lambda^T = \epsilon$, with ϵ small positive value, set here equal to 10^{-6}. According to (20), ξ_t^* can be thought as an application of the HP filter to the indicator original series, with an end-of-sample-problem correction given by the term $(\bar{\xi}^* - \ddot{\xi}_t^*)$, that receives an increasing weight as the end of the sample is approached. For more details on this aspect, see Arnold (2004).

In Fig. 3, we plot the systemic risk indicator and its equilibrium value ξ^*, shadowing the periods in which the indicator lies above its equilibrium value and highlighting the relevant stylised facts affecting global financial systems.

The indicator peaks during the financial-economic instability periods of the last 17 years. Neglecting the first part of the sample, corresponding to a recovery period for which a historically moderate level for the indicator is observed, there are 3 periods in which ξ is over its equilibrium value, which are: 1998:2 - 1999:2, 2001:1 - 2003:2 and 2008:3 - 2009:3.

The identification of each period listed above has an immediate economic interpretation. The first is associated to the panic that spreads out immediately after the default on the Russian debt in August 1998; the second corresponds to the economic and financial slowdown of the early 2000, further deteriorated by the events of 9/11. The third identified period corresponds to the recent economic and financial downturn. The indicator crosses from below ξ_t^* during the third quarter of 2008[1] (corresponding to the default of Lehman Brothers in September 2008) and stayed over it till 2009:3, being the end of 2008 characterized by high market volatility and the begin of 2009 by a fragile macroeconomic context and uncertainty about the recovery. By the end of 2009, the indicator falls below its equilibrium value as a consequence of the temporary recovery of the financial markets and the improvement of macroeconomic fundamentals especially in USA. However, in the first semester of 2010 and more markedly towards the end of 2011, the indicator shows a tendency to approach again its equilibrium value: this corresponds to when difficulties on the sovereign debt crisis experienced by peripheral European countries become apparent, spreading throughout the Euro Area and ultimately affecting the whole system.

3. Monetary policy and systemic risk

In this section, we report an empirical analysis on the interactions between systemic events and monetary policy decisions by the FED and the ECB.

We expand the Taylor rule to assess the sensitivity of the target interest rate to a systemic factor to be added to the canonical inflation rate and output gap variables. In principle, under severe systemic instability, an easing of monetary policy is expected, coherently with the mission statements of both Institutions. Indeed, the FED mission (FED, 1917) points out, among its macro-areas of intervention, the aim of "*maintaining the stability of the financial system and containing systemic risk that may arise in financial markets*". On the other hand, the main objective of the ECB is to maintain price stability and, in addition, "*Acting also as a leading financial authority, we aim to safeguard financial stability and promote European financial integration*" (ECB, 2011)

[1] The dynamics of the indicator described so far appear very close to the dynamics of the 1-year VaR of the distribution of the defaults for the overall economy, as proposed by IMF (2009).

In this paper, we evaluate the impact of systemic risk as an exogenous risk factor to both FED and ECB.

It is widely recognized that the 2007-2009 crisis originated in the US and affected the Euro Area at a later stage primarily through the financial system. The current sovereign debt crisis, however, also highlights the need of cooperative monetary effort to ensure global stability. Relying on the filtered systemic risk behavior displayed in Fig. 3, periods of high and low systemic risk are defined and monetary interventions under the two regimes are tested.

3.1. Model formulation

To empirically test the previous arguments, let us consider:

$$i = f(\pi, y, \xi) \tag{21}$$

where i is the target interest rate, π is the inflation rate, y is the output gap and ξ is the systemic risk indicator. We estimated both a cointegrated relationship and an equilibrium correction model (ECM) respectively of the form:

$$i_t = \phi + \eta t + \psi' Z_t + \epsilon_t \tag{22}$$

$$\Delta i_t = \omega + \sum_{l=1}^{p} \rho_l \Delta i_{t-l} + \sum_{l=0}^{p} \theta_l' \Delta Z_{t-l} + \delta \epsilon_{t-1} + u_t \tag{23}$$

where $Z_t \equiv [\pi_t \;\; y_t \;\; \xi_t]$ is a vector of explanatory variables, t represents a deterministic trend, while ϵ_t and u_t are white noise processes. We evaluate three alternative model specifications. The first model (MS1) is estimated considering just inflation and output gap as explanatory variables, that is $Z_t \equiv [\pi_t \;\; y_t]$, the second model (MS2) is estimated considering also the systemic risk indicator as explanatory variable, that is $Z_t \equiv [\pi_t \;\; y_t \;\; \xi_t]$. The final model (MS3) is estimated distinguishing between the case in which the systemic risk indicator is above its equilibrium value from the case in which it is not, that is $Z_t \equiv [\pi_t \;\; y_t \;\; \xi_t^+ \;\; \xi_t^-]$, where:

$$\xi_t^+ \equiv \begin{cases} \xi_t & \text{if } \xi_t \geq \xi_t^* \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

$$\xi_t^- \equiv \begin{cases} \xi_t & \text{if } \xi_t < \xi_t^* \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

MS1 allows us to check whether the systemic indicator is indeed relevant for monetary policy. MS2 is the benchmark. MS3 enables us to verify whether FED and ECB react differently to systemic risk, depending on the extent that ξ is above or below its equilibrium value.

In the empirical application, the system (22)-(23) is estimated starting from generalized unrestricted models (GUM) with $p = 5$ consistently with the empirical macroeconomic literature. The GUMs are then reduced to parsimonious correctly specified representations by controlling for the presence of structural breaks, by means of Autometrics^{TM} (Doornik, 2009; Castle, Doornik, and Hendry, 2011), an automatic procedure for model selection available in PcGive^{TM}.

We test for the presence of structural breaks by including in our model the following dummies:

$$B_{j,t}^M \equiv I_{\{t \geq j\}} \tag{26}$$

$$B_{j,t}^T \equiv (t - j + 1) I_{\{t \geq j\}} \tag{27}$$

with $j = 1, \ldots, T$, date of the break, and where $I_{\{\cdot\}}$ is the indicatrix function. $B_{j,t}^M$ and $B_{j,t}^T$ are designed to capture breaks in the mean and in the trend, accordingly. The estimation using Autometrics is run fixing a restrictive target size of 1% for the model selection procedure. The final selected model is then chosen using the Schwarz (SC), the Hannan-Queen (HQ) and the Akaike (AIC) Information Criteria.

3.2. Data description

The sample period for the FED model spans over 1995:1–2011:4, while for ECB over 1999:1–2011:4. As for the target interest rate, the quarterly average of the Fed Funds Rates and the Euro OverNight Index Average (EONIA) are considered for the FED and the EBC, respectively.

In the FED model, following Taylor (1993), Judd and Rudebusch (1998) and Hayford and Malliaris (2005), we specify the inflation rate as annualized 4-th order moving average of the percentage rate of change of the GDP deflator:

$$\pi_t \equiv 100 \left\{ \left[1 + \frac{1}{4} \sum_{i=1}^{4} \left(\frac{P_{t-i+1}}{P_{t-i}} - 1 \right) \right]^4 - 1 \right\} \tag{28}$$

where P_t is the quarterly series of the GDP deflator.

Inflation in the Euro Area is measured by the quarterly average of the one-year growth rate of the Harmonized Index of Consumer Prices (HICP), as in Gerlach-Kristen (2003).

Following Hayford and Malliaris (2005), the Congressional Budget Office (CBO) estimate of the potential GDP is used in the construction of the output gap for United States, while for the Euro Area the estimate provided by the HP filter is employed (see Section 2.1.).

Refer to Tab. 3 and Tab. 4 for the details on the data series. Descriptive statistics for the time series employed in the estimations are reported in Tabs. 5-6, while the plot of the series is in Figs. 4-5.

[Tabs. 3-6 about here.]

[Figs. 4-5 about here.]

From the graphical inspection of the series, there is evidence of different regimes affecting the interest rate series. In the case of the Fed Funds rates, the most notable turning points in the monetary conditions were in early 2000, in mid-2004 and in the second part of 2007. Similarly, for the ECB, we can distinguish phases of accommodating monetary policy, as in the period 2001–2005 and since late 2008 on, from periods characterized by restrictive decisions. For both institutions, the reaction to the early-2000s slowdown and to the global financial crisis 2007-2009 are immediately apparent.

In the following two sections we focus on the behavior of the FED and ECB, to explore the differences in the timing, the magnitude and the reasoning of their policy interventions.

3.3. Empirical results for the FED

We start our analysis by estimating the long-run relation as defined in (22). From the alternative models, after the reduction with Autometrics we obtain the following parsimonious specification (standard errors are reported in parenthesis):

$$
\begin{aligned}
i_t \;=\; & \underset{(0.280)}{4.738} \;-\; \underset{(0.013)}{0.073}\; t \;+\; \underset{(0.106)}{0.825}\; \pi_t \;+\; \underset{(0.044)}{0.365}\; y_t \\
& -\; \underset{(0.305)}{1.155}\; B^M_{2001:3} \;+\; \underset{(0.354)}{2.240}\; B^M_{2009:2} \\
& -\; \underset{(0.030)}{0.140}\; B^T_{2001:2} \;+\; \underset{(0.044)}{0.602}\; B^T_{2004:4} \;-\; \underset{(0.044)}{0.650}\; B^T_{2007:2}
\end{aligned}
\qquad (29)
$$

The estimated parameters are statistically significant and consistent with the economic theory. Namely, the coefficients of π_t and y_t are positive, implying a restrictive reaction in case of rising inflation and/or overheated economic growth. However, the coefficient associated to the GDP deflator is not greater than 1 and thus it does not confirm what expected from the original formulation of the Taylor Rule. This may reflect the choice of the inflation measure as highlighted by Hayford and Malliaris (2005).

Our estimates are stable to the change at the head of the Board of the FED in early 2006. This has been tested by substituting in (22) ψ with $\psi + \psi_{gr} B^M_{2006:1}$, where ψ_{gr}, referring to the Greenspan period, is not significant.

The long term decreasing trend is correctly detected by the trend component included in the model. Notice how the detected breaks are consistent with the features outlined in the Fig. 4. In particular, $B^T_{2001:2}$, $B^T_{2004:4}$ and $B^T_{2007:2}$ capture the turning points in the monetary conditions. Note that the systemic risk indicator does not appear in the long run relationship. A comparison between the long run component and the actual data is proposed in Fig. 6.

[Fig. 6 about here]

To test for the stability of the cointegration vector we employ a KPSS residual-based test suitable for the presence of structural breaks, that takes the form:

$$T^{-2}\hat{w}^{-2}\sum_{t=1}^{T}\left(\sum_{j=1}^{t}\hat{\epsilon}_j\right)^2 \tag{30}$$

where $\hat{w}$ is a consistent estimate of the long run variance of $\{\epsilon_t\}_{t=1,\ldots,T}$. Following Mogliani (2010), four alternatives are proposed for the kernel function employed in the estimation of the long run variance. The results are reported in Tab. 7. Bootstrap and fast double bootstrap p-values (Davidson et al., 2007) are provided. The four tests confirm the stability of the cointegrating vector (see Tab. 7).

[Tab. 7 about here]

In a second stage, the ECM formulation (23) is estimated, including the first difference of the detected breaks in (22). The inclusion of dummy variables on large residuals avoid misspecification problems for 2 model specifications out of the 3 considered. Namely, running the standard misspecification test to check for the presence of autocorrelation, heteroskedasticity and normality of the residuals, there is evidence of no misspecification in MS2 and MS3, while the estimates for MS1 shows hetoroschedasticity in the residuals. We thus employ the SC, the HQ and the AIC jointly to choose between the correctly specified alternative formulations. MS3 is the preferred model as it can be seen in Tab. 8.

[Tab. 8 about here]

The final selected model is:

$$
\begin{aligned}
\Delta i_t \;=\; & \underset{(0.045)}{0.014} + \underset{(0.086)}{0.701}\ \Delta i_{t-1} - \underset{(0.068)}{0.337}\ \Delta i_{t-4} \\
& + \underset{(0.093)}{0.316}\ \Delta p_t + \underset{(0.054)}{0.126}\ \Delta y_t - \underset{(0.057)}{0.197}\ \Delta y_{t-1} \\
& - \underset{(0.257)}{0.827}\ \Delta \xi^{+}_{t-1} - \underset{(0.247)}{1.192}\ \Delta \xi^{+}_{t-5} - \underset{(0.278)}{0.711}\ \Delta \xi^{-}_{t-1} \\
& - \underset{(0.082)}{0.480}\ \hat{\epsilon}_{t-1} \\
& - \underset{(0.077)}{0.204}\ \Delta B^{T}_{2001:2} + \underset{(0.110)}{0.440}\ \Delta B^{T}_{2004:4} - \underset{(0.095)}{0.329}\ \Delta B^{T}_{2007:2} \\
& - \underset{(0.264)}{1.127}\ D_{2008:4}
\end{aligned}
\tag{31}
$$

$$T = 62 \quad R^2 = 87.4\% \quad \hat{\sigma} = 0.190$$

$$AR(4) = 0.237 \quad ARCH(4) = 0.129 \quad NORM = 0.902 \quad HT = 0.040$$

where AR is the Breusch-Godfrey LM test for residual serial-correlation, ARCH is the Engle test for the presence of ARCH effects, NORM is the Doornik-Hansen test for normality of residuals and HT is the White test for heteroscedasticity. P-values are reported.

All coefficients but the constant are significant at a 1% significance level. The model is correctly specified and provides a good fitting of the data. Fig. 7 reports a comparison between actual and equilibrium values.

[Fig. 7 about here]

The error correction term $\hat{\epsilon}_{t-1}$ is statistically significant and negative. The changes in the US target rates are driven by an autoregressive component, changes in the cyclical indicator and the inflation rates, and the first difference of the systemic indicator. In this setting, the breaks detection captures the monetary regime shifting, while the indicator captures short term reactions to increasing systemic risk.

Thus, there is evidence that the FED reacts to changes in systemic risk conditions, which influence monetary decision up to lag 5. The coefficients of the lagged $\Delta\xi_t$ terms, as expected, have negative sign since an increase in the riskiness of the system is likely to induce an expansionary decision by the monetary authorities. The reaction is different depending on whether the systemic risk is above or below its equilibrium value. This is supported by both the dominance of MS3 on MS2 and by the magnitude of the coefficients referred to $\Delta\xi^{+}_{t-1}$ and $\Delta\xi^{-}_{t-1}$.

3.4. Empirical results for the ECB

In this section, we focus on the model specifications for ECB, following the same strategy as for the FED. Using the model reduction Autometrics, the estimation of the long-run relationship is:

$$\begin{aligned} i_t \; = \; & \underset{(0.325)}{3.191} - \underset{(0.122)}{0.393}\, t + \underset{(0.087)}{0.411}\, \pi_t + \underset{(0.026)}{0.466}\, y_t \\ & - \underset{(0.162)}{1.259}\, B^{M}_{2001:4} - \underset{(0.132)}{0.618}\, B^{M}_{2003:3} \\ & + \underset{(0.146)}{0.685}\, B^{T}_{1999:4} - \underset{(0.037)}{0.279}\, B^{T}_{2001:1} - \underset{(0.016)}{0.192}\, B^{T}_{2008:4} \end{aligned} \tag{32}$$

The estimated coefficients are consistent with the economic theory and close to those in the FED model. The magnitude of the inflation elasticity is coherent with what estimated in Gerlach and Lewis (2011). In this case too, the systemic indicator is not significant in the long run, and the detected breaks are at well known turning points in the monetary policy regimes. As in the FED case, the four KPSS residual-based tests employed confirm the stability of the cointegrating vector.

[Tab. 9 about here]

A comparison between the actual and the equilibrium term is reported in Fig. 8.

[Fig. 8 about here]

The ECM specification (23) is then estimated. Based on the results of information criteria reported in Tab. 10, MS3 is the selected model and it is reported below:

$$
\begin{aligned}
\Delta i_t \;=\; & \underset{(0.098)}{0.263} + \underset{(0.063)}{0.374}\,\Delta i_{t-1} \\
& + \underset{(0.103)}{0.295}\,\Delta\pi_t - \underset{(0.121)}{0.518}\,\Delta\pi_{t-1} + \underset{(0.112)}{0.230}\,\Delta\pi_{t-3} \\
& + \underset{(0.054)}{0.301}\,\Delta y_t + \underset{(0.035)}{0.101}\,\Delta y_{t-5} - \underset{(0.239)}{0.685}\,\Delta\xi^{+}_{t-1} \\
& - \underset{(0.124)}{0.616}\,\hat{\epsilon}_{t-1} \\
& - \underset{(0.149)}{0.546}\,\Delta B^{M}_{2001:4} - \underset{(0.138)}{0.466}\,\Delta B^{M}_{2003:3} - \underset{(0.103)}{0.283}\,\Delta B^{T}_{2001:1}
\end{aligned}
\tag{33}
$$

$$T = 46 \quad R^2 = 93.5\% \quad \hat{\sigma} = .117$$

$$AR(3) = 0.908 \quad ARCH(4) = 0.586 \quad NORM = 0.030 \quad HT = 0.960$$

[Tab. 10 about here]

The model is well specified, the error correction term is statistically significant and negative, and short run dynamics of the interest rates are governed by the inflation, the cyclical indicator, and the first difference of the one-period lagged systemic risk indicator, when it is above its equilibrium value. The relative coefficient is negative, thus the ECB shows evidence of reacting with easing monetary decisions to increasing systemic risk. Fig. 9 shows a comparison between actual and fitted values.

[Fig. 9 about here]

There is clear evidence of the superiority of the model specification MS3 for both the Central Banks. In the next section, we evaluate how the FED and the ECB reacted to shifts in the riskiness of the system.

3.5. Reactions to systemic instability

The aim of this section is to compare the reactions of the FED and the ECB to systemic risk events. Relying on the estimated models in Section 3.3.-3.4., we quantify the magnitude and analyze the timing of the policy decisions of the two Central Banks.

Let $\Delta Z^{\xi}_{t,j}$ with $j = FED, ECB$ be the regressors referred to ξ in the FED and the ECB model respectively.

In either the models, the null hypothesis that the residuals are normally distributed can not be rejected, that is $\hat{u}_{t,j} \sim \mathcal{N}(0, \sigma^2_j I)$. Hence, the estimated parameters are also normally distributed:

$$\hat{\theta}^{\xi}_j \sim \mathcal{N}\left(\theta^{\xi}_j, \Sigma_{\theta^{\xi}_j}\right) \tag{34}$$

where $\Sigma_{\theta^{\xi}_j}$ is the variance/covariance matrix of θ^{ξ}_j, which in absence of misspecification, is consistently estimated as:

$$\hat{\Sigma}_{\theta^{\xi}_j} = \hat{\sigma}^2_j \left(\Delta Z^{\xi}_{\cdot,j}{}' \Delta Z^{\xi}_{\cdot,j}\right)^{-1} \tag{35}$$

The estimated reactions to systemic risk are defined as:

$$\Delta\hat{i}^{\xi}_{t,j} \equiv \hat{\theta}^{\xi}_{j}{}'\Delta Z^{\xi}_{t,j} \tag{36}$$

Combining the previous results:

$$\Delta\hat{i}^{\xi}_{t,j}\Big|\Delta Z^{\xi}_{t,j} \sim \mathcal{N}\left(\theta^{\xi}_{j}{}'\Delta Z^{\xi}_{t,j}, \Delta Z^{\xi}_{t,j}{}'\Sigma_{\theta^{\xi}_{j}}\Delta Z^{\xi}_{t,j}\right) \tag{37}$$

Thus, under the null hypothesis $H_0 : \Delta\hat{i}^{\xi}_{t,j} = 0$:

$$\Delta\hat{i}^{\xi}_{t,j}\left(\Delta Z^{\xi}_{t,j}{}'\Sigma_{\theta^{\xi}_{j}}\Delta Z^{\xi}_{t,j}\right)^{-1/2}\Big|\Delta Z^{\xi}_{t,j} \sim \mathcal{T}(v) \tag{38}$$

where $\mathcal{T}(\nu)$ is the t-Student distribution with ν degrees of freedom, where $v = T-k$, with T the number of observations and k is the number of parameters estimated in the model.

The significant reactions to systemic risk are plotted in Fig. 10. Significance is evaluated using the result above, with the usual 1% significance level.

[Fig. 10 about here]

The sharper reactivity by the FED with respect to the ECB is immediately apparent. In particular, accommodative responses were given to the Russian crisis in late 1998, during the early 2000s slowdown and in coincidence with the recent financial crisis. A cyclical re-stabilizing behavior is evident, too. Note the case of 2009:4, where systemic risk have triggered an accommodative reaction, which was compensated by a reaction of opposite sign to rising inflation.

Instabilities have prompted less interventions by the ECB rather than by the FED. Namely, there is evidence that the European Central Bank reacted to the early 2000s financial and economic slowdown, but, more evidently, it responded to the recent financial crisis. Particularly evident is the joint reaction in 2008:4, when the FED and the ECB, together with other 5 industrialized countries' Central Banks (Canada, England, Switzerland, Sweden and Japan) decided for a joint intervention to face the panic spreading on the markets.

3.6. Robustness checks using the VIX and local cyclical indicators

In this section, we report a sensitivity analysis by comparing the performance of the global systemic risk indicator with respect to the VIX index, considered as a benchmark indicator. We also evaluate Central Banks reaction when only local cyclical indicators are considered in the definition of systemic risk.

VIX Indicator. The VIX provides a 30-days ahead volatility measure for the US stock market, being its value derived by S&P500 option contracts with 30 days to maturity. It is a popular measure of stock market uncertainty, capable to provide an accurate forecast of future volatility (see Blair, Poon and Taylor, 2001).

We look at the VIX index in the period in which the systemic risk indicator has been evaluated. The quarterly average of the index is considered and the corresponding trend component estimated via the HP filter. Fig. 11 provides a comparison between the indicator and the quarterly average of the VIX, together with the respective long run values.

[Fig. 11 about here]

The two indicators have the same long run dynamic behavior. However, from a closer inspection, a few important discrepancies can be highlighted. There are two notable periods when the VIX peaked over its trend, while on the contrary the indicator stays below it: they are the second half of 1997 and of 2007, associated to the Asian crisis and the US subprime crisis respectively. As argued in Section 2.3., these two periods are associated with country or sector specific crises, which are not relevant in systemic terms. Furthermore, this emphasizes the fact that high volatile markets are a necessary, but not sufficient, condition for systemic risk to increase. On the other hand, sluggish volatility on the markets does not imply an immediate contraction in systemic risk, as the period 2008-2009 shows.

Based upon the analysis above, we perform a robustness check for the two models reported in Eq. (31) and Eq. (33).

Let $\Delta Z^{\xi}_{t,j}$, with $j = FED, ECB$, be the regressors referred to ξ in the FED and the ECB model, Eq. (31) and Eq. (33) respectively:

$$\Delta Z^{\xi}_{t,FED} \equiv \left[\Delta\xi^{+}_{t-1} \;\; \Delta\xi^{+}_{t-5} \;\; \Delta\xi^{-}_{t-1}\right] \tag{39}$$

$$\Delta Z^{\xi}_{t,ECB} \equiv \Delta\xi^{+}_{t-1}. \tag{40}$$

Let θ^{ξ}_{j} denote the corresponding estimated parameters, V_t be the quarterly average of the VIX index at time t and V^{*}_{t} the corresponding trend component extracted via the HP filter. As in the case of ξ_t, define:

$$V^{+}_{t} \equiv \begin{cases} V_t & \text{if } V_t \geq V^{*}_{t} \\ 0 & \text{otherwise} \end{cases} \tag{41}$$

$$V^{-}_{t} \equiv \begin{cases} V_t & \text{if } V_t < V^{*}_{t} \\ 0 & \text{otherwise} \end{cases} \tag{42}$$

The robustness check consists in the inclusion of the term $\left(\Delta Z^{V}_{t,j} - \Delta Z^{\xi}_{t,j}\right)$ in each of the two models, where:

$$\Delta Z^{V}_{t,FED} \equiv \left[\Delta V^{+}_{t-1} \;\; \Delta V^{+}_{t-5} \;\; \Delta V^{-}_{t-1}\right] \tag{43}$$

$$\Delta Z^{V}_{t,ECB} \equiv \Delta V^{+}_{t-1} \tag{44}$$

Denote as δ^{V}_{j} the coefficients corresponding to the extra-term $\left(\Delta Z^{V}_{t,j} - \Delta Z^{\xi}_{t,j}\right)$.

Under the null hypothesis $H_0 : \theta^{\xi}_{j} = \delta^{V}_{j}$ there is superiority of the VIX index to the systemic risk indicator in explaining interest rates dynamics.

The null hypothesis is rejected for both models with a high confidence level (with $p-value = 0.0001$ for the FED and $p-value = 0.0061$ for the ECB, respectively). Furthermore, the partial adjusted R^2 associated with $\left(\Delta Z^{\xi}_{t,j}, \Delta Z^{V}_{t,j}\right)$ is $(60.44\%, 4.59\%)$ for the FED model and $(21.78\%, 0.47\%)$ for the ECB model. Finally, when testing the null hypothesis that the coefficients of $\left(\Delta Z_{t,j}^{\xi}, \Delta Z_{t,j}^{V}\right)$ are jointly insignificant, the p-values are $(0.0001, 0.6187)$ for the FED and $(0.0062, 0.7048)$ for the ECB. Thus, there is a clear statistical evidence of the superiority of the risk indicator with respect to the VIX index.

Local cyclical indicators. A further robustness analysis was performed to check whether FED and ECB reacted differently to systemic risk, when in addition to financial variables only local cyclical indicators were considered as components of the systemic risk indicator. The analysis was carried out in the same way as described above for the VIX. In Fig. 12, we report the systemic risk indicator with the local cyclical indicators for US and Euro Area respectively. The main finding is that the pattern of the reaction functions of the two institutions does not change, though there is evidence of higher recation of two institutions to local macroeconomic factors, as Fig. 13 shows. Details on the robustness check are not reported but available from authors upon request.

[Figs. 12-13 about here]

4. Conclusions

In this paper, we proposed a comprehensive indicator able to measure systemic risk at a global level. The indicator is constructed by integrating the dynamics of international financial and commodity markets with signals emerging from the economic cycle. Based upon the 1995-2011 crisis events, our indicator interpreted quite accurately recent financial history. We also showed that financial markets severe downturns and increasing volatility is not sufficient to explain the overall systemic risk in the economy.

We then evaluated the interaction of the indicator with monetary policy decisions undetaken by the FED and the ECB. There is evidence that expansionary decisions adopted by the FED were led by riskiness of the system, while the ECB showed some reluctance to give up its role in maintaining price stability, except during the recent period of economic and financial instability. The response of the monetary authority is not prompted by the conditions in the equity market alone, but also by commodity market dynamics and the economic cycle, with all these factors are captured by the systemic risk indicator we proposed.

This paper extends the scope of systemic risk analysis allowing to identify important differences between FED and ECB monetary conducts during a prolonged period of economic and financial crisis. First, it will be interesting to extend the analysis to UK, to include an evaluation of the of monetary policy decision by the Bank fo England. Second, our analysis can be extended to early warning signals also in the light of the current sovereign debt crisis. Further, the sensitivity analysis reported in this paper can be enriched by considering both the Libor-OIS spread (the difference between LIBOR and the Overnight Indexed Swap) and the Composite Indicator of Systemic Stress (Hollo, Kremer and Lo Duca, 2012). This is part of an ongoing research agenda.

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ID Index	***Asset Class***	***Area***	***Name***	***Ticker***	***Base date***
1	Equity	United States	MSCI USA	MSUSAML	31-Dec-69
2	"	Euro Area	MSCI EMU	MSEMUIL	31-Dec-87
3	"	United Kingdom	MSCI UK	MSUTDKL	31-Dec-69
4	"	Japan	MSCI JAPAN	MSJPANL	31-Dec-69
5	"	Emerging Countries	MSCI EM	MSEMKFL	31-Dec-87
6	Bond	United States	JPM GBI US	JGUSAU$	01-Sep-03
7	"	Euro Area	JPM GBI EUR	JGEUAEE	01-Sep-03
8	"	United Kingdom	JPM GBI UK	JGUKAU£	01-Sep-03
9	"	Japan	JPM GBI JAP	JGJPAJY	01-Sep-03
10	"	Emerging Countries	JPM EMBI+ COMP	JPMPTOT	31-Dec-93
11	Corporate	United States	ML US CORP	MLCORPM	30-Mar-73
12	"	Euro Area	ML EMU CORP	MLCPLCE	31-Dec-96
13	"	United Kingdom	ML CORP ALL UK	ML£CAUL	07-May-04
14	"	Japan	ML JAP CORP	MLJPCPY	15-Sep-05
15	"	Emerging Countries	ML EMRG CORP	MLICD0$	31-Dec-04
16	Money Market	United States	JPM US CASH 3M	JPUS3ML	31-Dec-85
17	"	Euro Area	JPM EURO CASH 3M	JPEC3ML	22-Oct-86
18	"	United Kingdom	JPM UK CASH 3M	JPUK3ML	31-Dec-85
19	"	Japan	JPM JAP CASH 3M	JPJP3ML	31-Dec-85
20	"	Emerging Countries	ML USD EMRG SOV	MLIGD0$	31-Dec-04
21	Commodity	*none*	S&P GSCI	CGSYSPT	31-Dec-69

Table 1: Market data for the construction of the systemic risk indicator (source: Datastream^{TM}).

Time series	***Ticker***	***Frequency***	***Base date***
GDP US	USGDP...D	Quarterly	1950:1
GDP Euro Area	EKGDP...D	Quarterly	1995:1
GDP UK	UKGDP...D	Quarterly	1955:1
GDP Japan	JPGDP...D	Quarterly	1980:1
Citigroup Economic Surprise Indices	TBCESIR	Daily	01-Jan-03

Table 2: Data for the estimation of the cyclical indicators used in the construction of the systemic risk indicator (source: Datastream^{TM}).

Variables	***Name***	***Ticker***	***Frequency***	***Remark***
Target rate	US Federal Funds	FRFEDFD	Daily	Middle rate
Inflation Index	US GDP DEFLATOR	USONA001E	Quarterly	Seasonally Adj.
GDP	US GDP	USGDP...D	Quarterly	Constant Price Seasonally Adj.
Potential GDP	US CBO Forecast - Potential GDP	USFCGDPPD	Quarterly	Constant Price Seasonally Adj.

Table 3: Variables employed in the FED model (source: Datastream^{TM}).

Variables	***Name***	***Ticker***	***Frequency***	***Remark***
Target rate	Euro OverNight Index Average (EONIA)	EUEONIA	Daily	Offered rate
Inflation Index	CPI (no energy and unprocessed food)	EKESCPXUF	Monthly	Seasonally Unadj.
GDP	EK GDP	EKGDP...D	Quarterly	Constant Price Seasonally Adj.

Table 4: Variables employed in the ECB model (source: Datastream^{TM}).

	i	π	y	ξ
Mean	3.347	2.085	-0.875	0.259
Standard deviation	2.235	0.723	2.830	0.266
Asymmetry	-0.243	0.124	-0.993	1.337
Kurtosis	1.433	2.747	2.960	3.764
Min	0.075	0.458	-7.429	0.025
Max	6.520	3.522	3.537	0.989
Normatility test	23.699 [0.0000]**	0.20576 [0.9022]	31.017 [0.0000]**	56.387 [0.0000]**

Table 5: Descriptive statistics (FED Model)

	i	π	y	ξ
Mean	2.585	1.713	0.076	0.285
Standard deviation	1.325	0.521	1.408	0.286
Asymmetry	-0.182	0.056	0.173	1.133
Kurtosis	2.040	1.815	2.603	3.094
Min	0.345	0.856	-2.850	0.025
Max	4.844	2.637	3.144	0.989
Normatility test	3.0474 [0.2179]	4.8367 [0.0891]	0.35648 [0.8367]	34.894 [0.0000]**

Table 6: Descriptive statistics (ECB Model)

LR variance kernel	***Stat***	***Bootstrap p-value***	***Fast Double Bootstrap p-value***
Bartlett	0.02181	0.53745	0.53895
Quadratic Spectral	0.01974	0.65157	0.65297
Parzen (Andrews and Monahan, 1992)	0.02228	0.53845	0.53835
Kurozumi (2002)	0.02227	0.58536	0.58816

Table 7: Test for the stability of the cointegration vector for different choices of the kernel function employed for the estimation of the long-run variance of the residuals (FED model). For details see Mogliani (2010).

	SC	***HQ***	***AIC***
MS1	-	-	-
MS2	0.527	0.403	0.323
MS3	0.145	-0.152	-0.343

Table 8: Information criteria for the alternative model specifications MS1, MS2 and MS3 (FED model). SC is the Schwarz Criterion, HQ is the Hannan-Quinn Criterion and AIC the Akaike Information Criterion.

LR variance kernel	***Stat***	***Bootstrap p-value***	***Fast Double Bootstrap p-value***
Bartlett	0.03616	0.21772	0.21582
Quadratic Spectral	0.03694	0.14071	0.13681
Parzen (Andrews and Monahan, 1992)	0.04497	0.05911	0.05601
Kurozumi (2002)	0.03963	0.20352	0.20182

Table 9: Test for the stability of the cointegration vector for different choices of the kernel function employed for the estimation of the long-run variance of the residuals (ECB model). For details see Mogliani (2010).

	SC	***HQ***	***AIC***
MS1	-0.639	-0.920	-1.085
MS2	-0.683	-0.989	-1.170
MS3	-0.771	-1.077	-1.258

Table 10: Information criteria for alternative model specifications MS1, MS2 and MS3 (ECB model). SC is the Schwarz Criterion, HQ is the Hannan-Quinn Criterion and AIC the Akaike Information Criterion.

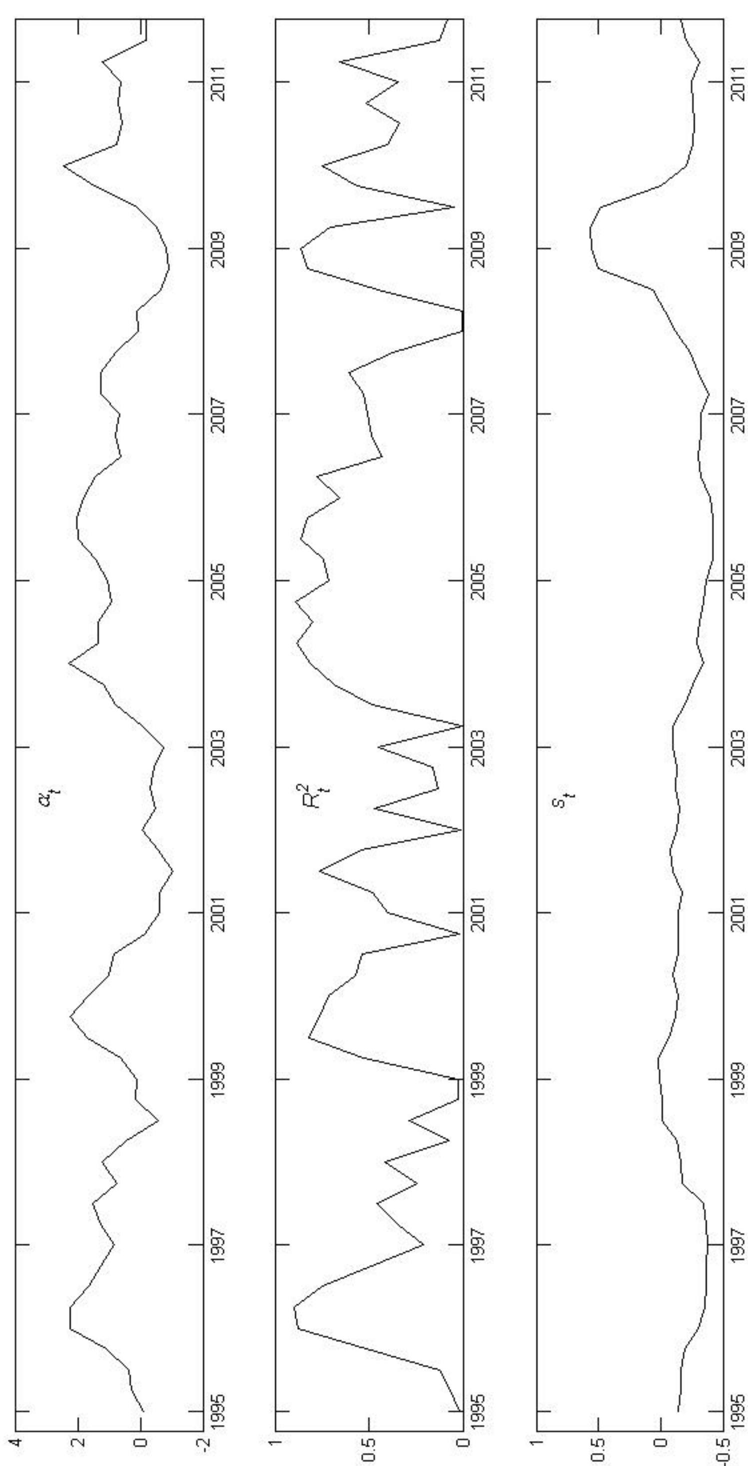

Figure 1: Plot of the estimated financial variables α, R^2 and s entering in the systemic risk indicator.

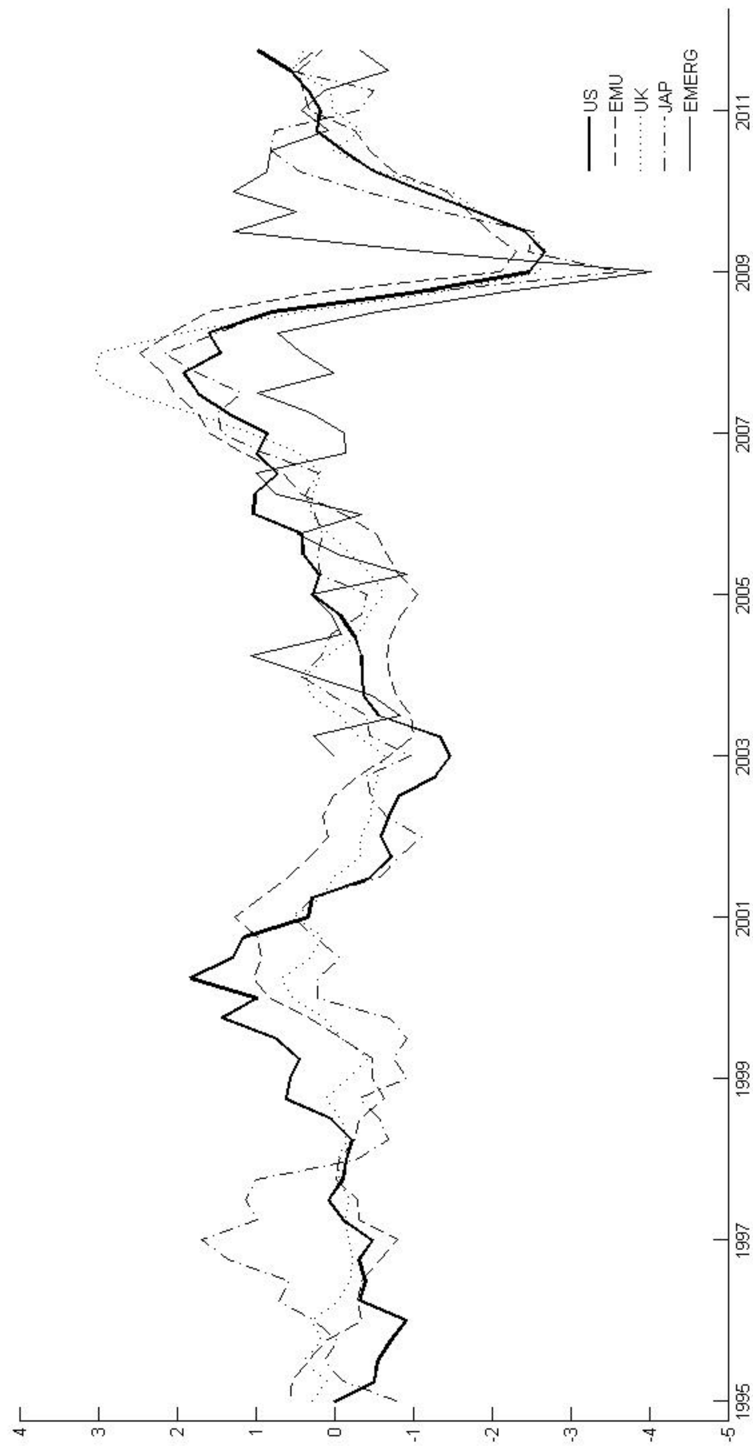

Figure 2: Plot of the normalized value of the cyclical indicators entering in the systemic risk indicator.

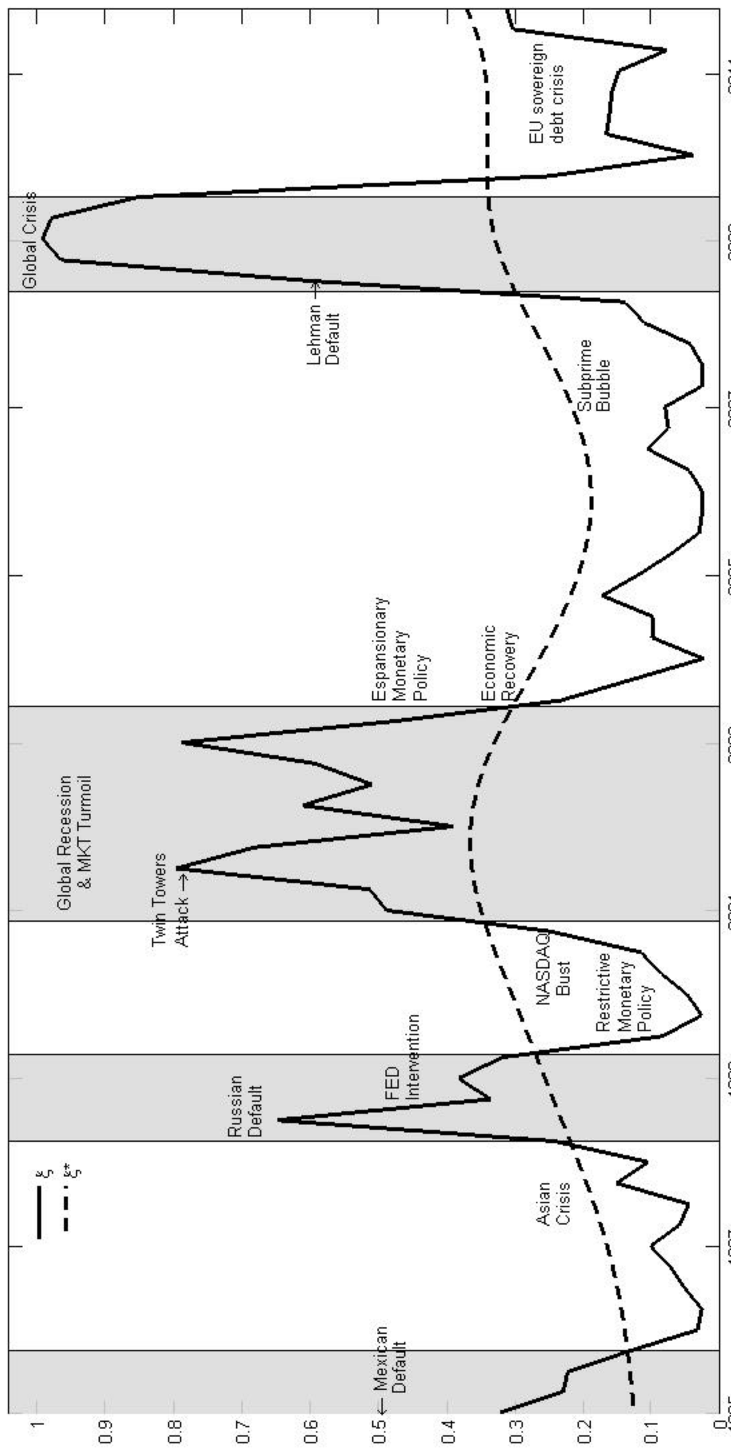

Figure 3: The systemic risk indicator and the recent financial history (1995:1–2011:4)

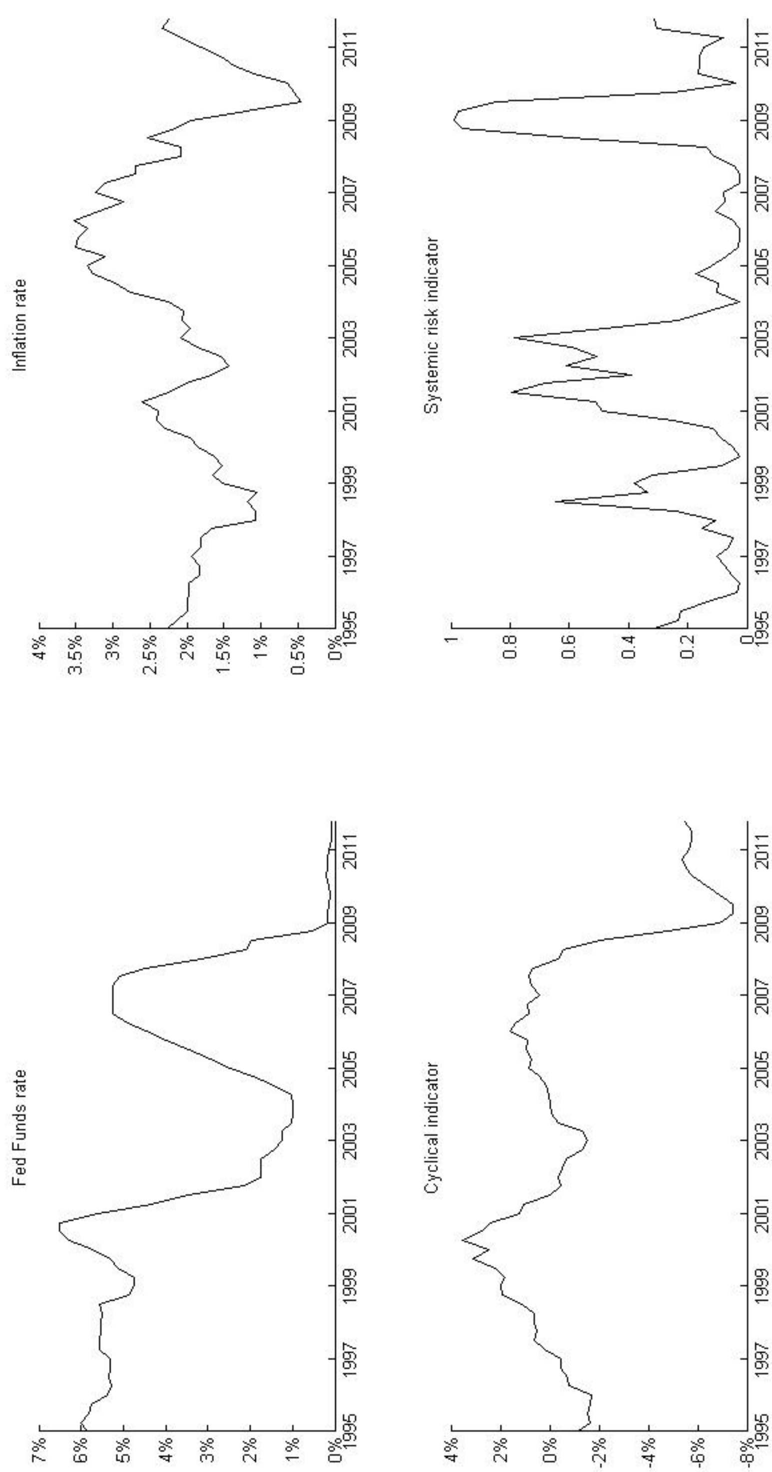

Figure 4: Plot of the series used in the FED model.

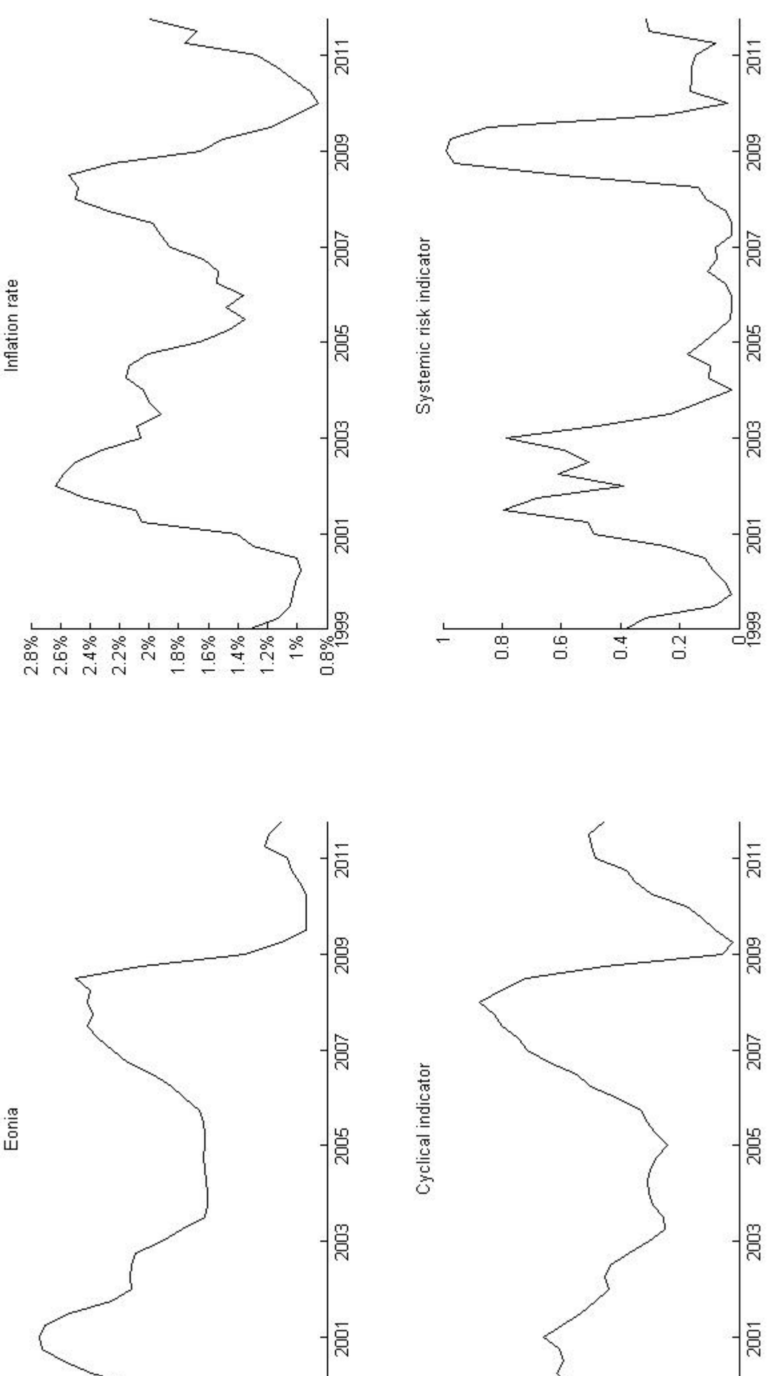

Figure 5: Plot of the series used in the ECB model.

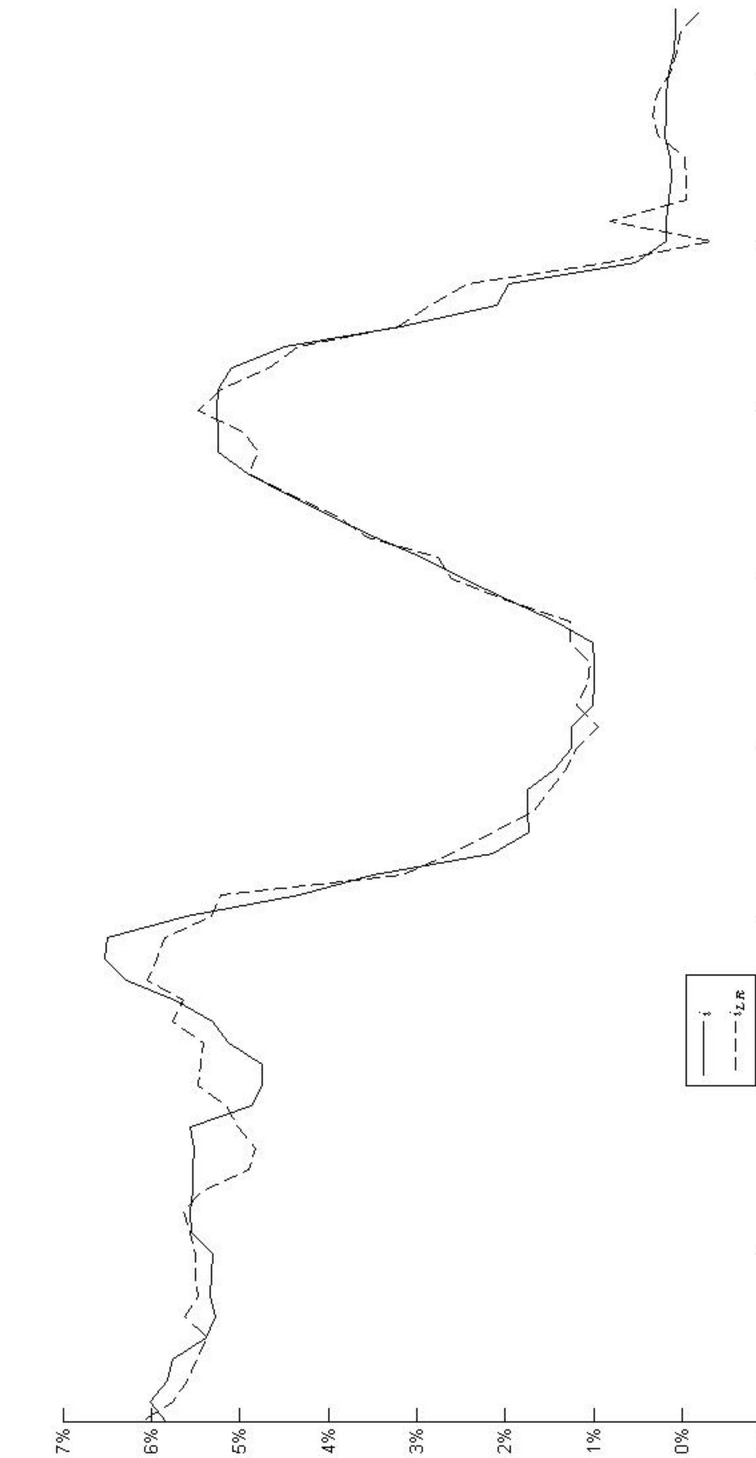

Figure 6: FED Funds Rates quarterly average vs. Long Run component.

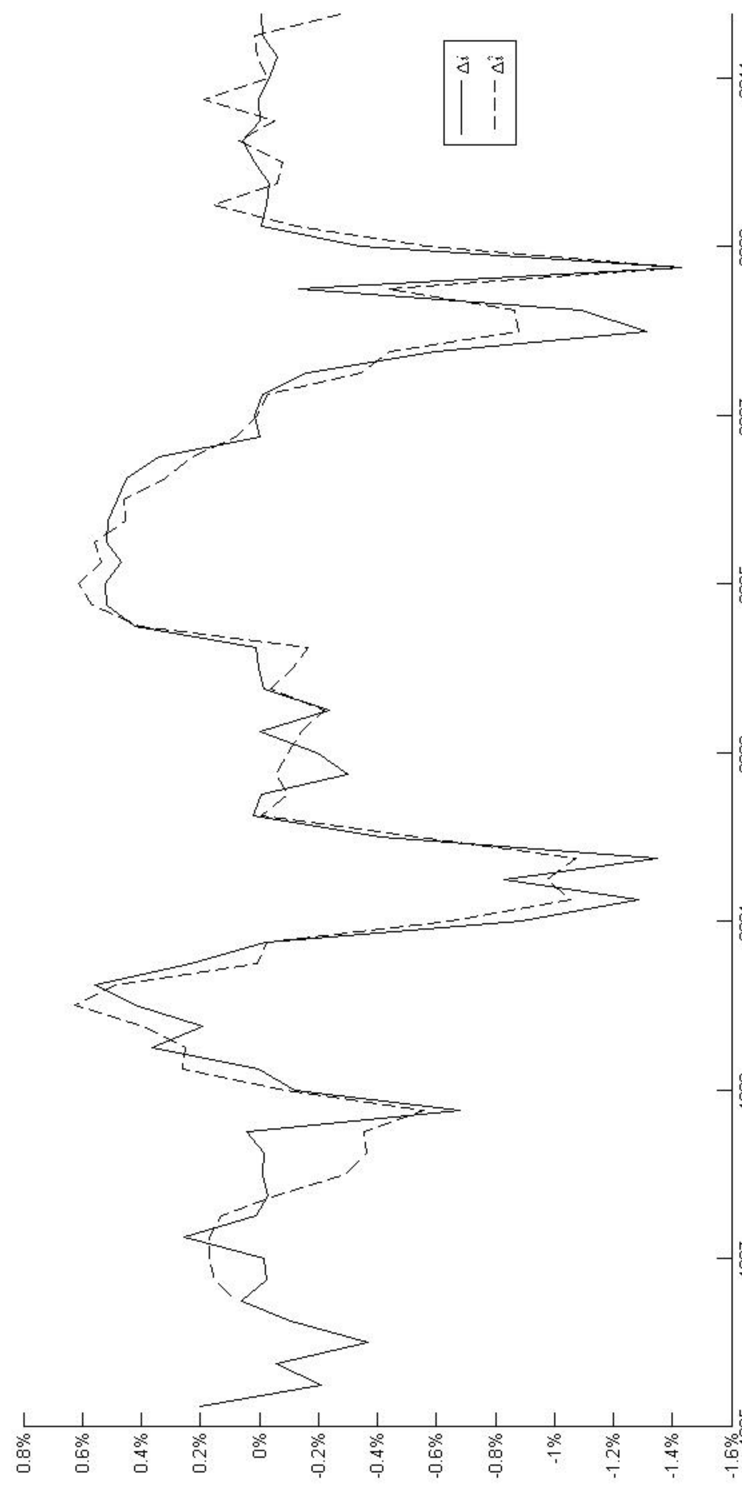

Figure 7: Actual-fitted comparison for the ECM (FED model).

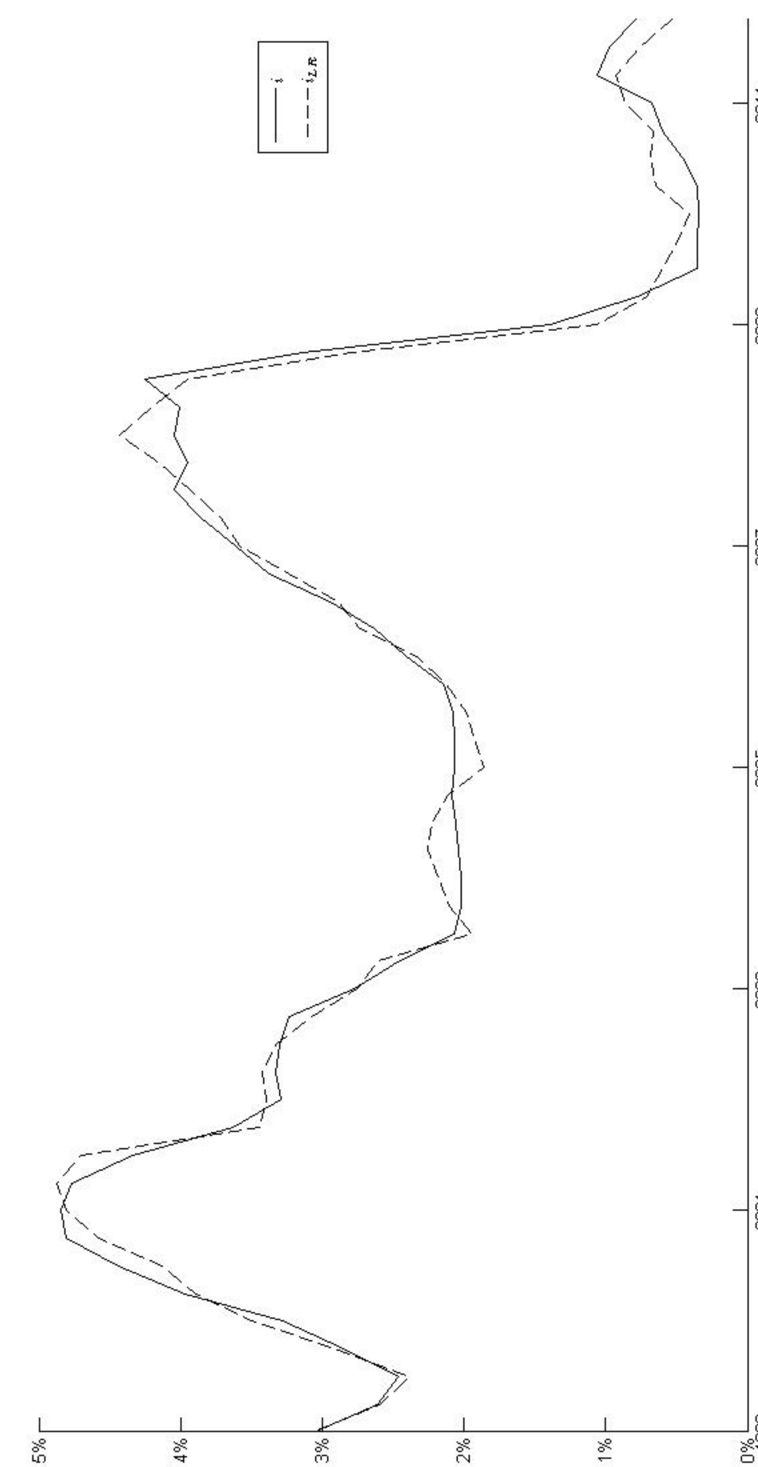

Figure 8: Eonia quarterly average vs. Long Run component.

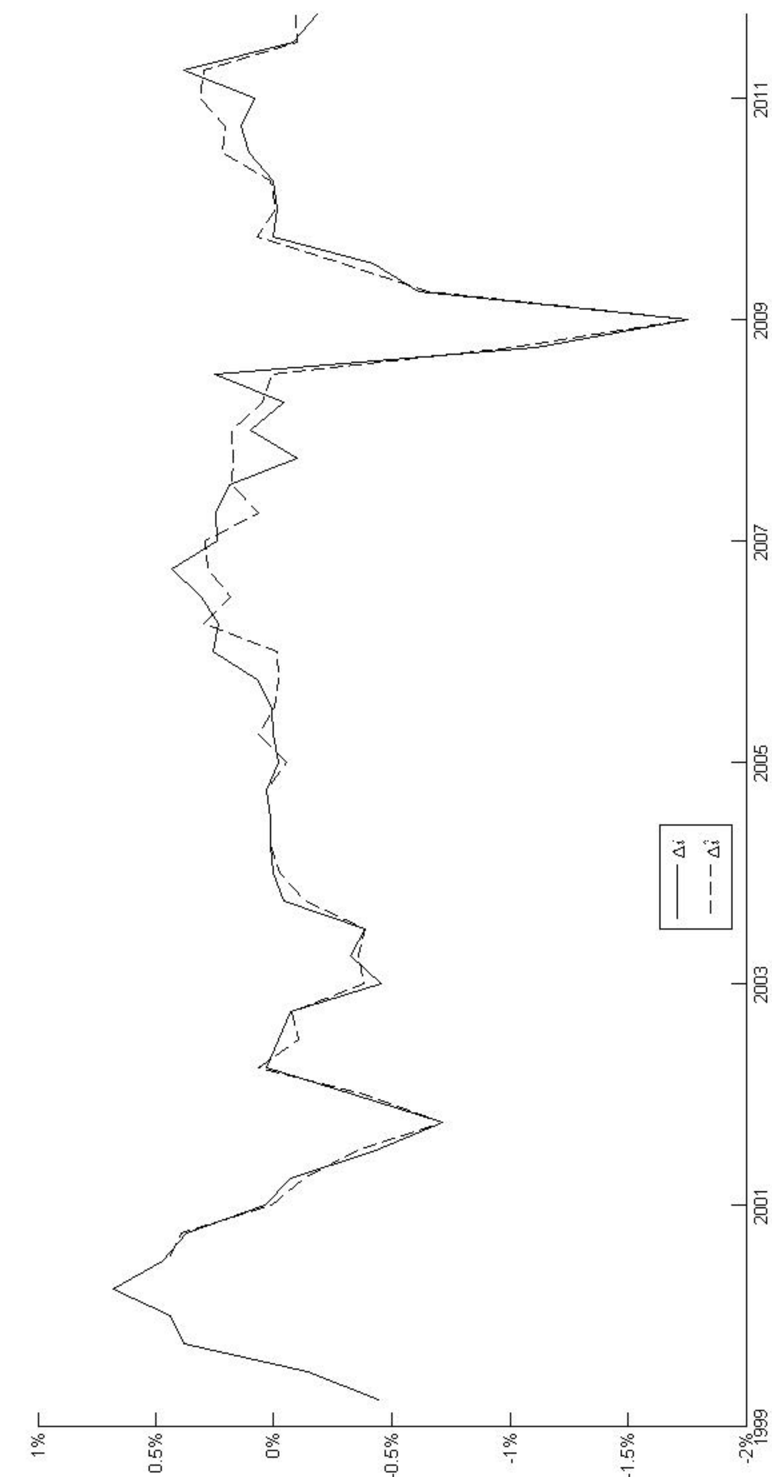

Figure 9: Actual-fitted comparison for the ECM (ECB model).

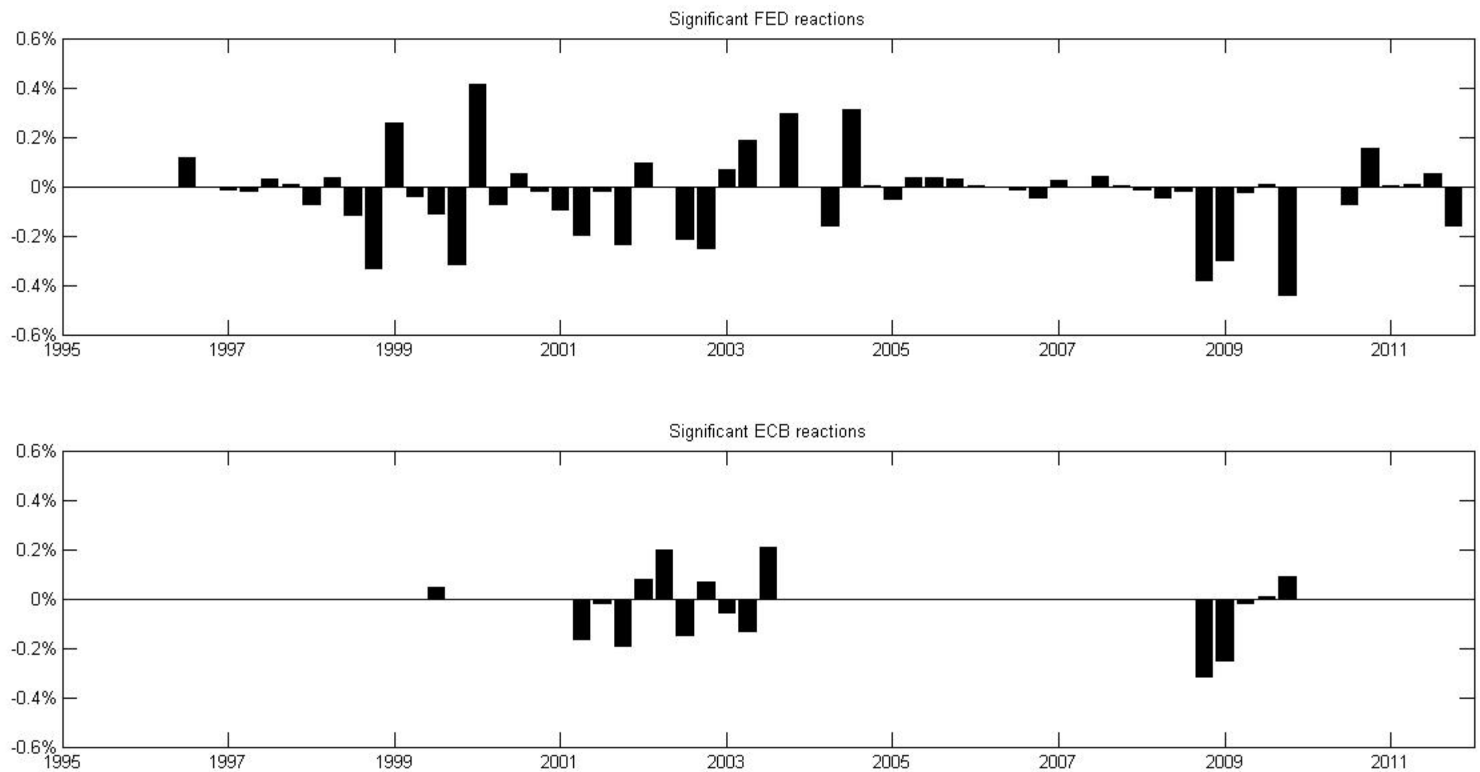

Figure 10: FED and ECB reactions to riskiness of the system computed by stressing the estimated models with the observed variations of the systemic risk indicator.

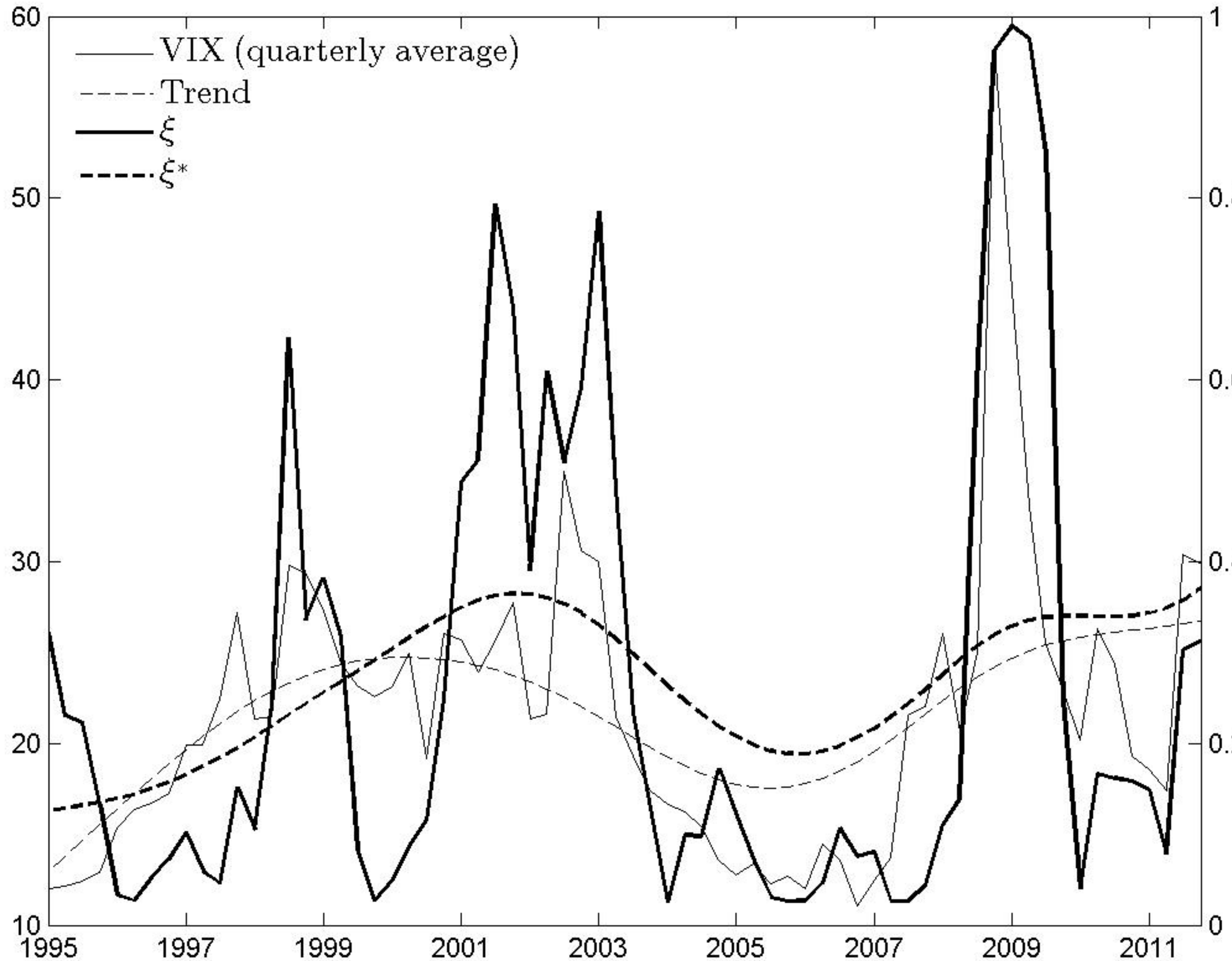

Figure 11: The systemic risk indicator (right axis) and the quarterly average of the VIX index (left axis) with their trend components.

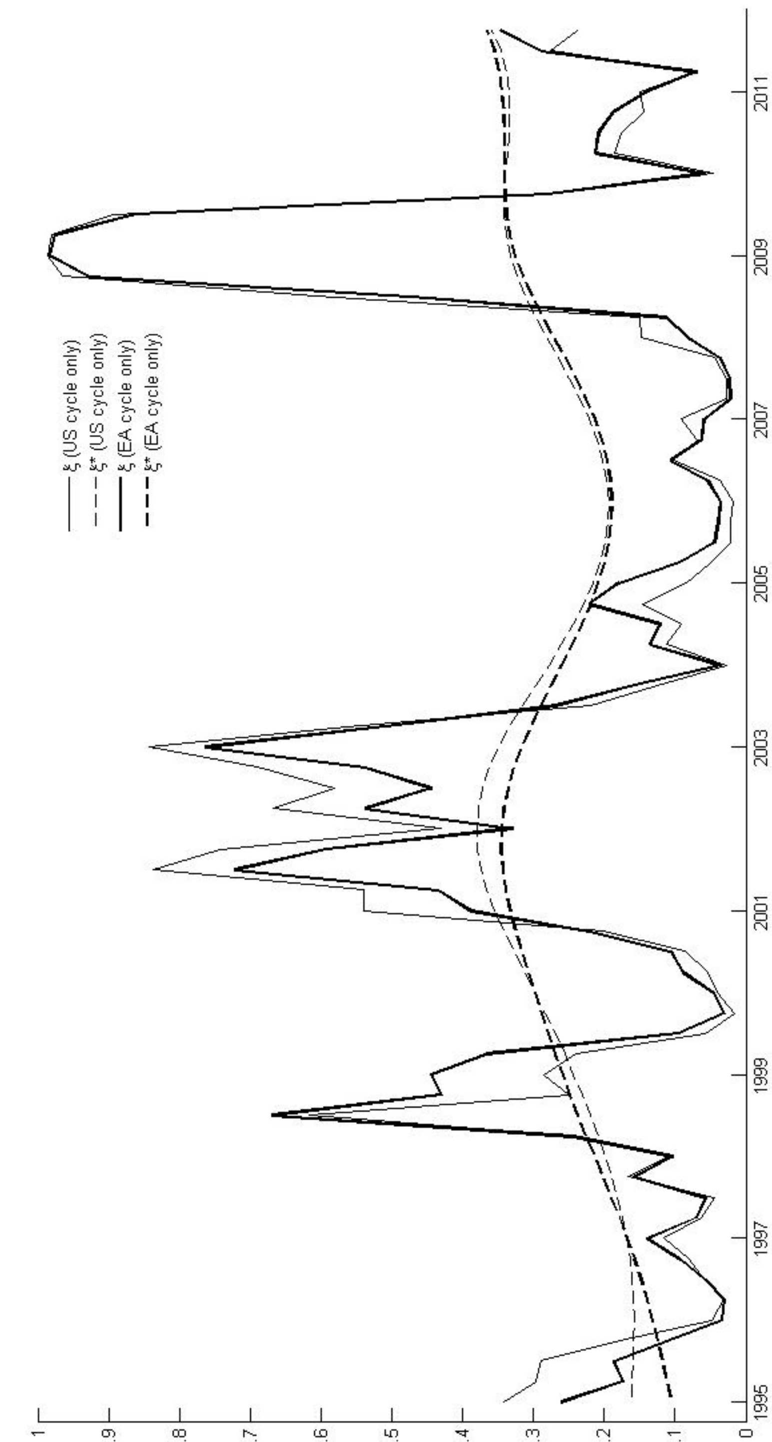

Figure 12: The systemic risk indicator with local cyclical indicators only (comparison between US and Euro Area).

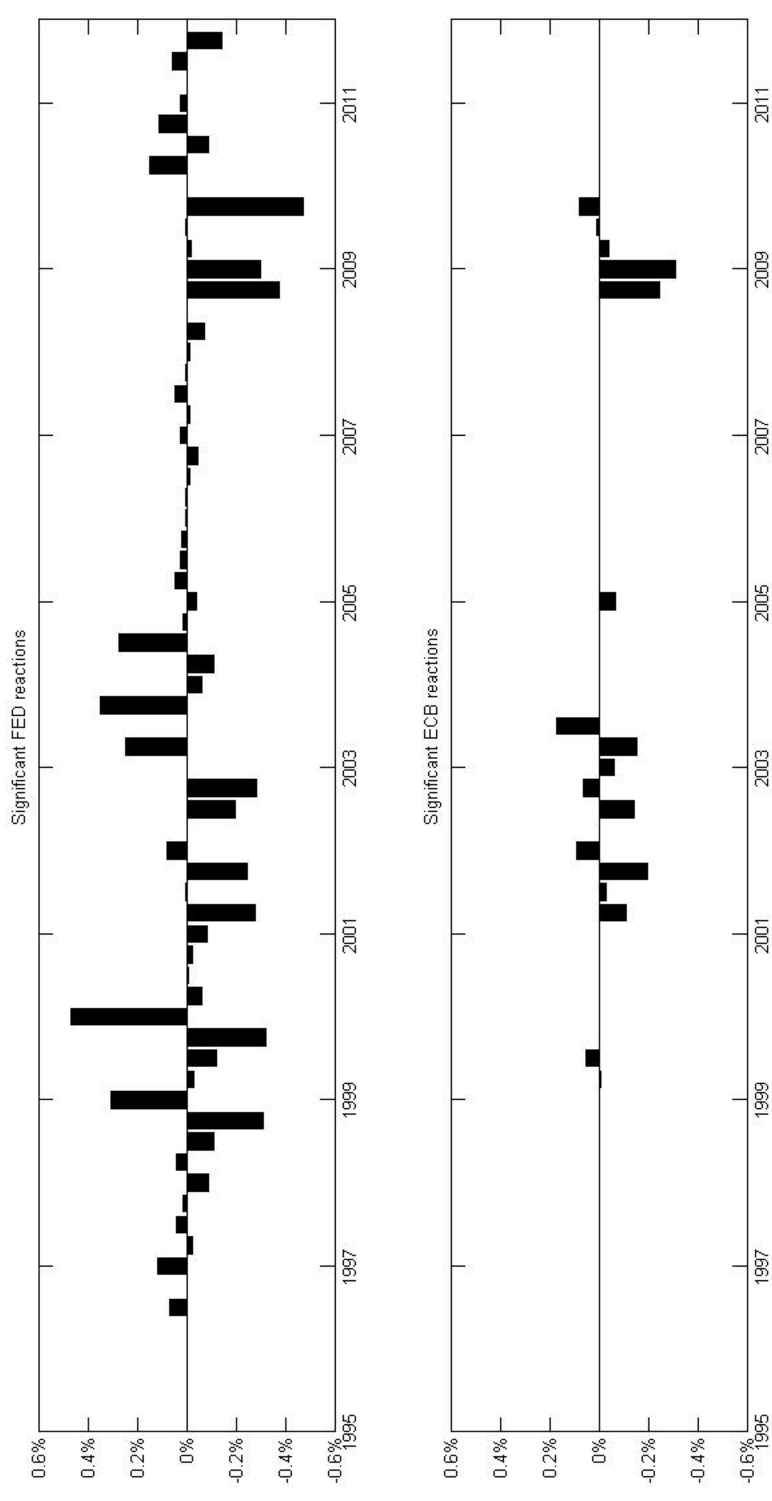

Figure 13: FED and ECB reactions to riskiness of the system computed by stressing the estimated model with the observed variations of the systemic risk indicator conatining only local cyclical components.