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Thesis title:

ESSAYS IN FINANCIAL ECONOMETRICS

PhD in ECONOMICS

Cycle XXI

Candidate's tutor PROF CARLO A. FAVERO

Year of discussion 2010

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Acknowledgments

A number of people contributed to the realization of this thesis.

Special thanks go to my supervisor, Prof Carlo Favero, for his expertise and countless valuable comments and ideas, and for enthusiastic supervision through all these years; I am grateful to Prof Giampiero Gallo for taking time to serve as my external reader and for all the suggestions, and and I also thank Luca Sala for useful discussions.

Part of this thesis was written while I was working as a Quant Analyst at Calyon CIB; I wish to thank particularly Pierre Castellani for the help and useful suggestions and for being always encouraging.

A particular thought goes to my amazing family, whose trust and love have made all this possible, and to Marco, for priceless moral and technical support.

Lastly, I will be always thankful to Giovanna and Marianna, for being there each and every day through my life and research experience. To them I dedicate this thesis.

Contents

Chapter 3

Business Cycle Forecasts and Stock Market Fluctuations: How much does the Stock Market Price?

Introduction

This thesis is organized in three chapters which cover different applications of econometrics techniques to three challenging issues.

The first chapter, *Measuring Risk Contagion and Interdependence: CoVaR*, deals with the problem of being able to capture risk spillovers among financial institutions analyzing both short-run and long-run equilibrium components which characterize the dependence existing among financial institutions. Due to the substantial failure of standard measures of risk to perform as global measures, Adrian and Brunnermeier (2009) propose a new measure of risk - the *CoVaR* -. In this chapter we share the idea of providing an alternative measure of risk and propose a new multivariate framework in which both the existence of common stochastic trends at the price level and the presence of volatility spillovers are successfully taken into account. We apply our method to a set of five commercial banks and corresponding value-weighted indices which represent the sector surrounding each of these institutions - (*sector indices*) - and provide not only an accurate measure of risk but we are able also to distinguish between two types of dynamics identifying the existence of a long run equilibrium for banks equity prices. Relying on the estimation of bivariate conditional covariance matrices, this model also proposes a new alternative approach to the estimation of short run contemporaneous dependence relationships which does not require any restriction to be imposed on the structural representation to gain identification of the parameters of interest. In this chapter we argue that the *CoVaR*, which constitutes a new and more global measure of risk with respect to standard *VaR*, brings along some degrees of incompleteness; we therefore propose a model which can capture channels of interdependence, distinguishing between long run and short run dependencies, delivering an accurate measure of exposure to risk especially during periods of financial turmoils. Despite analyzing standard spillover effects which are not new to the literature, we argue that there is an interesting dynamic happening at the price level which is worth being taken into account to verify the existence of a double transmission channel which pertains both instantaneous and long run dependency relations.

The second chapter, *A Three-Factor GARCH Model for Term Structured Daily Returns*, explores the strong similarity existing between the term structure of interest rates and the term structure of financial returns proposing a generalized method for the analysis of the conditional variance of the latter. We estimate a model in which the term structure of financial returns is summarized using three time-varying latent factors - as proposed in Nelson-Siegel (1987) and re-interpreted in Diebold and Li (2000) - which can, in the case of daily returns, display GARCH behavior. Given the substantially different structure that characterizes daily log returns with respect to interest rates along the time dimension, we have to reject the possibility to use in full the specification designed for the analysis of the yield curve confirming the fundamental unpredictability of financial returns. On the other hand, to address the issue of modeling the conditional variance of such series, we augment the model with a GARCH specification showing that there is room for an appreciable reduction of the dimensionality of problems related to the estimation of the conditional variance. The empirical exercise, conducted on a panel covering about three years of daily log returns for Oil contracts at different maturities, shows that such a parsimonious framework is a simple and easy to implement tool to analyze the term structure of daily returns and their variation over time. Particularly, out-of-sample forecasts of the variance of the whole panel is easily computed providing important tools for risk analysis. Lastly, this approach allows to handle easily computations - such as volatility impulse response functions - in a multivariate setting.

The last chapter, *Business Cycle Forecasts and Stock Market Fluctua-*

tions: How Much does the Stock Market Price?, explores the possibility that different perceptions on the same economic variable are priced-in into the stock market. In this chapter we assert that despite the dependence between the stock market and economic aggregates, financial and macroeconomic variables respond to different but yet equivalently important sets of information. If this is true then the same set of variables will be perceived differently if we look at it from a financial or a macroeconomic perspective; moreover, it is possible to construct excess optimism variables which capture such difference in perception. We argue that stock market fluctuations price-in such difference in perception at different time horizons showing that quarterly growth rates of excess optimism variables constructed for inflation and income are significant predictors of quarterly growth rates of stock market returns at different horizons. In order to capture the information embedded into what we refer to as the macroeconomic and financial perspectives we employ generalized dynamic factor models as in Forni *et al* (2005) to extract signals from two large macroeconomic and financial panels of US data. We run the exercise on a panel of US monthly variables. Our results suggest that the market responds negatively to the excess optimism on income when this happens in the short to medium run perceiving the variable as a source of instability; on the other hand, if the effect is persistent, meaning that it is captured up to the 1-year-ahead prediction, then this is interpreted as a positive piece of information which boosts the growth rate of stock market returns in the long term.

Measuring risk contagion and interdependence: *CoVaR*

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First version: Jul 2009, this version: Jan 2010

Abstract

Adrian and Brunnermeier (2009) propose a global measure of risk - the *CoVaR* - which copes with the inability of standard *VaR* to capture risk transmission among financial institutions. This paper shares the idea of providing an alternative measure of risk and proposes a new multivariate framework in which both the existence of common stochastic trends at the price level and the presence of volatility spillovers are successfully taken into account. Using daily data on five commercial banks not only we deliver an accurate measure of risk but we are able also to distinguish between two types of dynamics identifying the existence of a long run equilibrium for banks equity prices. Relying on the estimation bivariate conditional covariance matrices, this model also proposes a new alternative approach to the estimation of short run contemporaneous dependence relationships which does not require any restriction to be imposed on the structural representation to gain identification of the parameters of interest.

Keywords: Value at Risk, Conditional VaR; Risk Spillovers; Multivariate GARCH.

JEL Classification Numbers: C32, C15, G32, G01

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1 Introduction

Interdependence among financial institutions becomes particularly important during periods of distress, when losses tend to spread across institutions and the whole financial system becomes vulnerable. Moreover, especially during financial crises, episodes of contagion are not rare and need to be taken into account in order to analyze the overall health level of a financial system. In light of such phenomena, measuring the exposure toward risk of a given institution without considering all sources of risk spillovers would imply a significant loss of information that, as a consequence, would result in an incomplete measure.

The most commonly used measure of financial risk - the Value at Risk (*VaR*) - measures the dollar loss an institution may incur within a given confidence level. This measure, however, does not consider the institution as part of a system which might itself experience instability and spread new sources of systemic risk: the actual level of riskiness might then be seriously underestimated especially in presence of strong interrelation between institutions operating within the same sector.

In order to deal with this, Adrian and Brunnermeier (2009) propose a new more complete measure of risk which they define as the *CoVaR* and, more precisely, as the *VaR* of institution i conditional on institution j being in distress. In their definition this measure is able to capture alternative sources of risk which affect institution i even though they are not directly originated by it. If index i identifies the whole sector, then the difference between the *CoVaR* and the unconditional *VaR* - $\Delta CoVaR$ - captures the marginal non-causal contribution of a particular institution to the overall systemic risk, or, in other terms, its esternalities. Adrian and Brunnermeier compute the *CoVaR* on a set of financial institutions within a quantile regression framework which delivers almost directly the above mentioned measure.

Within this framework the prediction of a quantile regression of the financial sector $\hat{X}^{system,i}$ on a particular portfolio i is

$$\hat{X}^{system,i} = \hat{\alpha}^i + \hat{\beta}^i X^i \tag{1}$$

where $\hat{X}^{system,i}$ is the predicted value of a particular quantile conditional on institution i. When X^i is at its *VaR* level, equation (1) yields the *CoVaR*.

This paper argues that the *CoVaR*, which constitutes a new and more global measure of risk with respect to standard *VaR*, brings along some degrees of incompleteness which can be addressed reconsidering the problem of measuring risk from a different perspective. In the attempt of delivering a measure of conditional risk, in the sense of risk associated to the sector the institution operates within, we propose a model which can capture channels of interdependence, distinguishing between long run and short run dependencies, delivering an accurate [1] measure of exposure to risk especially during periods of financial turmoils.

Despite analyzing standard spillover effects which are not new to the literature, we argue that there is an interesting dynamic happening at the price level which is worth being taken into account to verify the existence of a double transmission channel which pertains both instantaneous and long run dependency relations. We apply our method to a set of five commercial banks and corresponding value-weighted indices which represent the sector surrounding each of these institutions (*sector indices*). The reason for which we are interested in long run equilibrium relationship between each bank and its corresponding sector index is in Figure 1 below. Here we plot the evolution of log equity prices of each individual bank against the log equity

[1] The degree of accurateness is analyzed in the reminder of this paper with respect to standard *VaR* measures

prices computed for the sector specific to each bank [2]. The scenario depicted in the graph provides the intuition behind the model which is going to be developed here, where we want to take into account the possibility that there exist common stochastic trends governing the price dynamic which can influence the degree of dependence of each bank on the surrounding environment and provide insight on the existence of a long run equilibrium within the same system. We show that a general framework in which both the price dynamic and the conditional second moments are modeled jointly produces a measure of risk which captures accurately both intrinsic exposure and risk propagation.

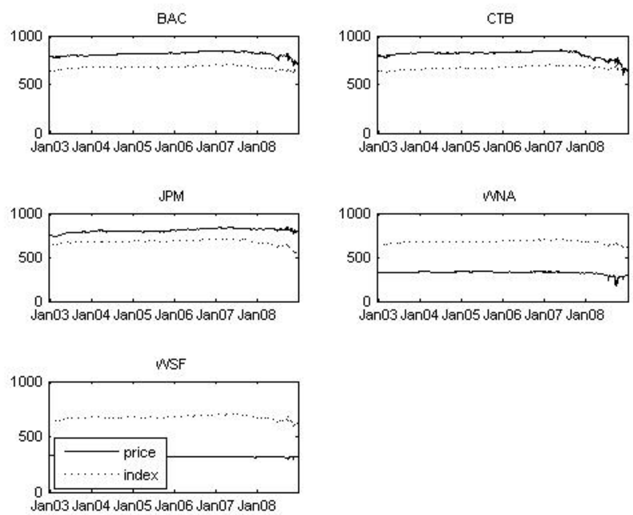

Figure 1: Log equity prices for each bank and its corresponding index. Whole sample.

The evidence that almost all major crises occurred in the past years - including the 1987 equity market crash - became global financial crises even

[2]Details on the construction of the index are in Section 2 of this paper.

though their origin is to be found in specific sectors, has been widely analyzed in several articles which particularly refer to the role that esternalities play in this settings (Brady (1988), Rubin, Greenspan, Levitt and Born (1999), Brunnermeier (2009)). We also refer to a large literature which has focused on *VaR* and volatility spillovers primarily modeled via multivariate GARCH. McAleer and Da Veiga (2008) analyze the importance of considering spillover effects when forecasting financial volatility, in particular when forecasting *VaR* thresholds. They compare several different models and show (2005, University of Western Australia) that the multivariate VARMA-GARCH model of Ling and McAleer (2003) and VARMA-asymmetric GARCH (or VARMA-AGARCH) model of Hoti et al. (2003) provided superior volatility and VaR threshold forecasts to their nested univariate counterparts, namely the GARCH model of Bollerslev (1986) and the GJR model of Glosten et al. (1992), respectively.

In order to deal with the over parametrization which characterizes such models when the number of assets included increases, several parsimonious models have been proposed: the constant conditional correlation (CCC) model of Bollerslev (1990), the varying conditional correlation (VCC) model of Tse and Tsui (2002), and the dynamic conditional correlation (DCC) model of Engle (2002), Engle and Sheppard (2001) which we use here. Important early contributions to this literature are Susmel and Engle (1994) and Lin, Engle, and Ito (1994). Recent papers on volatility spillovers include among others Savva, Osborn, and Gill (2005), Baur and Jung (2006), and Wongswan (2006); these papers generally analyze spillover effects between financial markets or geographical areas and use stock market indices with daily or weekly frequency.

The remainder of this paper is organized as follows. Section 2 defines the model used throughout the analysis with particular attention to the identification of the linkage between the system and each of its components. Section 3 defines the *CoVaR* in a GARCH framework and the alternative measure which is developed in this application. Section 4 displays the empirical findings and Section 5 concludes.

2 Exploring the linkage between each bank and the sector: identification

Adrian and Brunnermeier (2009) define the *CoVaR* as the Value at Risk of a given financial institution conditional on other institutions being in distress. Let the sector be identified by a set of N financial institutions and let b identify each of its components. The index which we will refer to as the *sector index* is constructed as a weighted average with bank specific weights depending on each institution's market value, in particular, following Pesaran *et al.* 2004 the index is computed in the following way:

$$P_{IDX_{b^*}} = \sum_{b \neq b^*} \omega_b P_{b,t} \tag{2}$$

where $P_{b,t}$ is the log equity prices of bank b; note at this stage that - by construction - the index for bank b^* depends on market value and equity prices of all banks in the sample but b^*.

Although the index constructed according to equation (2) does not contain any direct reference to the bank b^*, any simultaneous relation between $P_{IDX_{b^*}}$ and $P_{b^*,t}$ could still bring along serious identification issues primarily due to the fact that the way we construct the index does not make it strictly exogenous.

To see this point suppose that one is interested in estimating the following system of equations:

$$\Gamma X_t = k + \epsilon_t \tag{3}$$

where X_t is a matrix containing equity returns of each bank and the corresponding index ($X_t = [R_{b,t}, R_{IDX_b,t}]'$), k is the intercept term and

$$\Gamma = \begin{pmatrix} 1 & -\gamma \\ 0 & 1 \end{pmatrix}. \tag{4}$$

The system as it is allows for the identification of the parameter γ which captures the dependence of the bank on the sector, however, because of the index being not strictly exogenous, the parameter might still be not correctly estimated, in other words, we cannot capture consistently the contemporaneous relationship between each banks and the relevant sector. The procedure we propose here is to gather the identification of the parameter γ modeling the conditional covariance of each bank and its own sector equity returns and then use the information carried by the non constant conditional covariance matrix to compute the parameter of interest.

The model that we adopt here is in the following bivariate system:

$$\Delta Y_t = \Pi_0 + \Pi Y_{t-1} + \varepsilon_t \tag{5}$$

where $Y_t = [P_{b,t}, P_{IDX_b,t}]'$, P denotes equity prices, Π_0, and Π are matrices of coefficients, and $\varepsilon_t = [\varepsilon_{b,t}, \varepsilon_{IDX_b,t}]'$ with $\varepsilon_{b,t}$ being a vector of heteroskedastic bank-specific shocks. Equation (5) can be equivalently rewritten as

$$X_t = \Pi_0 + AB'Y_{t-1} + H_t^{1/2}\eta_t \tag{6}$$

where X_t is the matrix defined in equation (3), H_t is the conditional covariance matrix and $\eta_t = [\eta_{IDX_b,t}, \eta_{b,t}]' \sim N(0, I)$.

The system in equation (6) captures simultaneously a number of different effects. Parameters in $\Pi = AB$ pick the effect of the dynamic at the log price level on the evolution of equity returns, also, and more importantly, parameters in B identify the long run equilibrium between the bank and the sector while A determines the speed of adjustment towards the equilibrium level. On the other hand, the presence of the conditional covariance matrix H_t within the specification allows to define a structure for the time varying variance which will be crucial in the construction of the risk measure. Lastly, we argue that the same conditional covariance matrix can be used to derive the short run dependence relationship of the bank on the sector (γ in equation (4)). More formally, for each time t:

$$H_t = \begin{pmatrix} \Omega_{t,bb} & \Omega_{t,bIDX} \\ \Omega_{t,bIDX} & \Omega_{t,IDXIDX} \end{pmatrix} \tag{7}$$

then

$$\gamma_t = \frac{\Omega_{b,IDX}}{\Omega_{IDX,IDX}} \tag{8}$$

3 *CoVaR*

The *CoVaR* introduces a new measure of risk which aims to take into account the fact that particularly during financial crisis the losses tend to spread across financial institutions (Brady(1998), Rubin, Greenspan, Levitt and Born (1999), Brunnermeier(2008)). The most common measure of risk used by financial institutions - the *VaR* - delivers the dollar loss which may occur with a certain probability. This measure, however, fails to capture how much risk is due to the surrounding environment.

The *VaR* captures risk spillovers in an indirect way, to the extent that different institutions can be exposed to common factors of risk; however the *VaR*, as it is, fails to give insight on the identification of the common risk factors and, more importantly, does not provide any information related to co-dependence of risk. This paper shows that most of the interdependence and contagion effects can be captured using a measure of risk which is derived from a multivariate model which jointly models the mean and the variance of the bivariate process.

The $CoVaR_{i|j}$ is defined as the Value-at-Risk of institution i given that institution j is in distress, or more specifically, the *VaR* of institution i conditional on other institutions j being at their unconditional *VaR* level. Therefore, while *VaR* captures the tail risk of financial institutions from a partial equilibrium point of view, *CoVaR* is a summary statistic capturing tail risk dependency, which is arguably a more important measure of risk from a systemic risk point of view (Adrian *et al.* (2009)).

In this application we are going to proceed following two parallel analysis. To stress the importance of jointly modeling the variance of the bank and the sector, we will adopt both a univariate and a bivariate specification for H_t. In the univariate framework we detect interdependence as follows:

- compute VaR_i for all observations in the sample;
- select those equity returns for which $R_i \leq VaR_i$ (bad draws);
- compute VaR_j for all observations in the sample;
- select those equity returns for which $R_j \leq VaR_j$;

This procedure will allow to test whether there is any interdependence between the *VaR* of the single bank and the *VaR* of the whole system. On the other hand we detect contagion in the following way:

- compute VaR_i for all observations in the sample;
- select those equity returns for which $R_i \leq VaR_i$;
- select *only* those R_j which correspond to the bad draws;
- compute VaR_j only for these returns;

This second set of steps will deliver a measure of contagion between institutions i and j, in other words we obtain a measure equal to $VaR_j|R_i \leq VaR_i$ which is the $CoVaR_{j|i}$.

In the univariate specification the variance of the bank and the corresponding sector are modeled separately, with a univariate GARCH(1,1). This enables to model the two conditional variances without taking into account any cross relationship between the two series and any contagion effect will be pointed out using the four step procedure described above.

$$\begin{aligned}
e_{b,t} &= \sigma_{\eta_b,t}\eta_{b,t}; & (9)\\
\sigma^2_{\eta_b,t} &= \delta_0 + \delta_1\eta^2_{b,t} + \delta_2\sigma^2_{\eta_b,t-1}; & (10)\\
e_{IDX_b,t} &= \sigma_{\eta_{IDX_b},t}\eta_{IDX_b,t}; & (11)\\
\sigma^2_{\eta_{IDX_b},t} &= \delta_0 + \delta_1\eta^2_{IDX_b,t} + \delta_2\sigma^2_{\eta_{IDX_b},t-1} & (12)
\end{aligned}$$

In a second more complete specification, the conditional covariance matrix of the system as a whole - both the bank and its corresponding index - is modeled according to a bivariate DCC-GARCH(1,1,1).

$$\begin{aligned}
e_t &= H_t^{1/2}\eta_t; & (13)\\
H_t &= D_t P_t D_t & (14)
\end{aligned}$$

where

$$\begin{aligned}
D_t &= diag(h_{b,t}, h_{IDX_b,t}); & (15)\\
P_t &= (Q_t^*)^{-1/2}Q_t(Q_t^*)^{-1/2}; & (16)\\
Q_t^* &= diag(Q_t); & (17)\\
Q_t &= (1-a-b)S + a\eta_{t-1}\eta_{t-1}^{'} & (18)
\end{aligned}$$

$\eta_{t-1} = D_{t-1}^{-1}e_{t-1}$ are the standardized returns, $a > 0$, $b \geq 0$, $a + b \leq 1$ and S

is a positive definite matrix, typically the unconditional correlation.

Besides the clear advantage of being able to model the covariances as well, and thus delivering a tool for computing the long term dependence parameter γ, the multivariate GARCH implicitly captures the contagion effects originating the conditional measure of risk that Adrian and Brunnermaier define as the $CoVaR$.

4 Risk spillover in the financial sector

The theoretical setting discussed in the previous sections has been applied to a dataset containing daily equity returns for five commercial banks (Bank of America (BAC), Citibank (CTB), JP Morgan Chase (JPM), Wachovia (WNA) and Wells Fargo (WSF), source: Datastream) and spans the period from 17-Dec-2002 to 31-Dec-2008. The sector indices, specific to each of the five banks, are constructed as value-weighted averages as in equation (2); market value data with daily frequency are still from Datastream for the same time window. Once bank holidays are removed from the sample we are left with 1512 observations for each equity series. The sample is partitioned into two subsets with the forecast period starting on Aug-2007 which conventionally sets the beginning of the last financial crisis.

All risk measures are computed on a 1day basis: 1 day ahead forecasts of the conditional variances - both in the univariate and bivariate case - are computed updating the estimation sample at every new forecast. Then VaR measures are bootstrapped with a bootstrap sample of 10,000 observations per forecast.

The first interesting result is in the estimation of the Value-at-Risk in the univariate case. The most serious signal of inadequateness of such a measure is in the way it underestimates the risk, particularly when the financial system experiences heavy variations. To highlight this we construct violation indicator functions which take value 1 whenever the value of the return falls below the *VaR* threshold. Such an instrument will be used throughout the analysis to compare the performance of the different risk measures. Another, possibly more interesting effect that emerges from the estimation of univariate *VaR* but is not captured by it, is the regularity that characterizes violations. In the analysis concerning both banks and sector indices the violations, whose number is huge, tend to happen at the same point in time providing evidence for interdependence episodes: there are elements which influence simultaneously the performance of all the institutions operating within the same sectors causing violation clustering. Failing to take into account such dependence between institutions generally resolves in an inadequate measure and this is particularly true when these transmission channels are enhanced by financial instability. Details are in figures 3 and 4.

The second set of results refers to the computation of the *CoVaR* explicitly taking into account possible contagion effect, but still relying on a univariate estimate of the conditional variances. Because episodes of contagion interfere with institutions belonging to the same environment within the same time window, it is clear that conditioning on the sector being in distress isolates banks returns which perform worse than usual as (i.e. are below the unconditional *VaR* level). As a result, values for the *CoVaR* lie significantly below the univariate *VaR* levels reducing significantly the total number of violations in each of the cases considered; moreover, violation clustering disappears as a consequence of the conditioning process. These results show that the transmission of risk moves in both directions: on one hand institutions are influenced by the overall health level of their relative sector; on the other hand, sectors are sensible to variations at individual bank levels, therefore, it is crucial to take such interrelation into account when evaluating risk exposure. Violation functions in this case are in figures 5 and 6.

The performance of our proposed measure is reported in figures 7 and 8. The full bivariate framework, defined in equations (6) and (16) of Section 2, produces very similar results in terms of accurateness with respect to the explicit measure of contagion in figures 5 and 6 suggesting that it efficiently handles volatility spillovers caused by contagion episodes considering the whole sample of observations. Technically, estimating the VaR within the bivariate specification reduces the number of violations and also eliminates the clustering phenomenon because estimates of the covariance between each bank and the corresponding sector play an active role in defining the individual Value-at-Risk reducing the actual probability of falling below the threshold. Covariances capture volatility spillovers which, in turn, reflect into risk transmission, therefore, a model like the one proposed here produces directly the conditional and global risk measure suggested by Adrian and Brunnermeier (2009).

Also, and more importantly, this framework unlike the one quantile regression $CoVaR$, allows to analyze both contemporaneous relationships between each bank and the sector and long term equilibria. Figure 2 reports the short run and long run dependence parameters for each bank in the panel with respect to its own corresponding sector. The flat dotted line corresponds to the long run dependence while the time varying line is the γ_t parameter measuring how much each bank depends on its sector. It worth notice that without imposing any restriction on the coefficients this method not only provides insights on the degree of dependence of institutions towards the sector, but is also able to capture the reverse channel which measures the sensitivity of the sector with respect to each of its components. The picture shows clearly that, especially towards the end of our sample, when the effect of the crisis became more visible, the short run coefficient diverges from the long run one confirming the substantial instability governing the latter months of 2008. Such a discrepancy not only evidences the need of taking into account long run equilibrium component, but also provides a new interpretation on the nature of the short run variation.

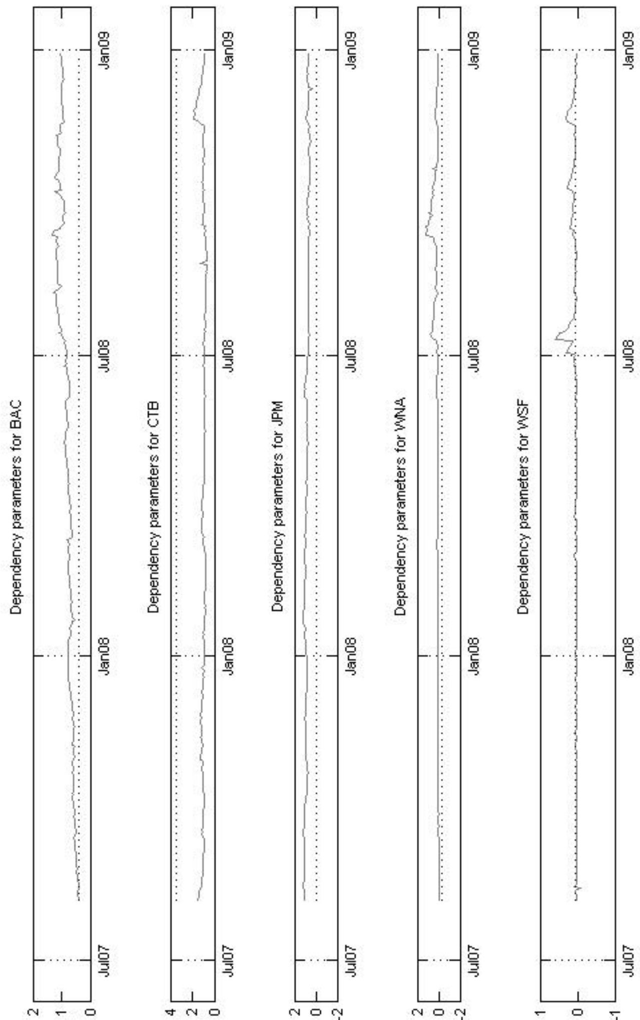

Figure 2: The short run time varying parameter is estimated using the information embedded in the conditional covariance matrix. The long run parameter is computed reparametrising the bivariate specification in equation (6).

5 Conclusion

Especially during financial turmoils, tail events tend to spread across financial institution; however, even the most commonly used measure of risk - VaR - fails to capture such risk spillovers among institutions underestimating the actual level of risk. Adrian *et al* (2009) propose to adopt a new measure of risk which is able to measure the dependence of one financial institution on the surrounding system and vice versa. The $CoVaR$, defined as the VaR of institution i conditional on institution j being in distress, is computed using regression quantiles.

This paper shares the idea of providing an alternative measure of risk and proposes a new multivariate framework in which both the dynamic at the price level and the presence of volatility spillovers are successfully taken into account. In this setting not only we deliver an accurate measure of risk but we are able also to distinguish between two types of dynamics identifying the existence of a long run equilibrium level for banks equity prices, with all the relevance that this has in terms of dynamic properties of the model. Relying on the estimation of the bivariate conditional covariance matrix, this model also proposes a new alternative approach to the estimation of such kind of short run contemporaneous dependence relationships - which are usually dealt with via Cholesky factorization - in more general setting, which does not require any restriction to be imposed on the structural representation to gain identification of the parameters of interest.

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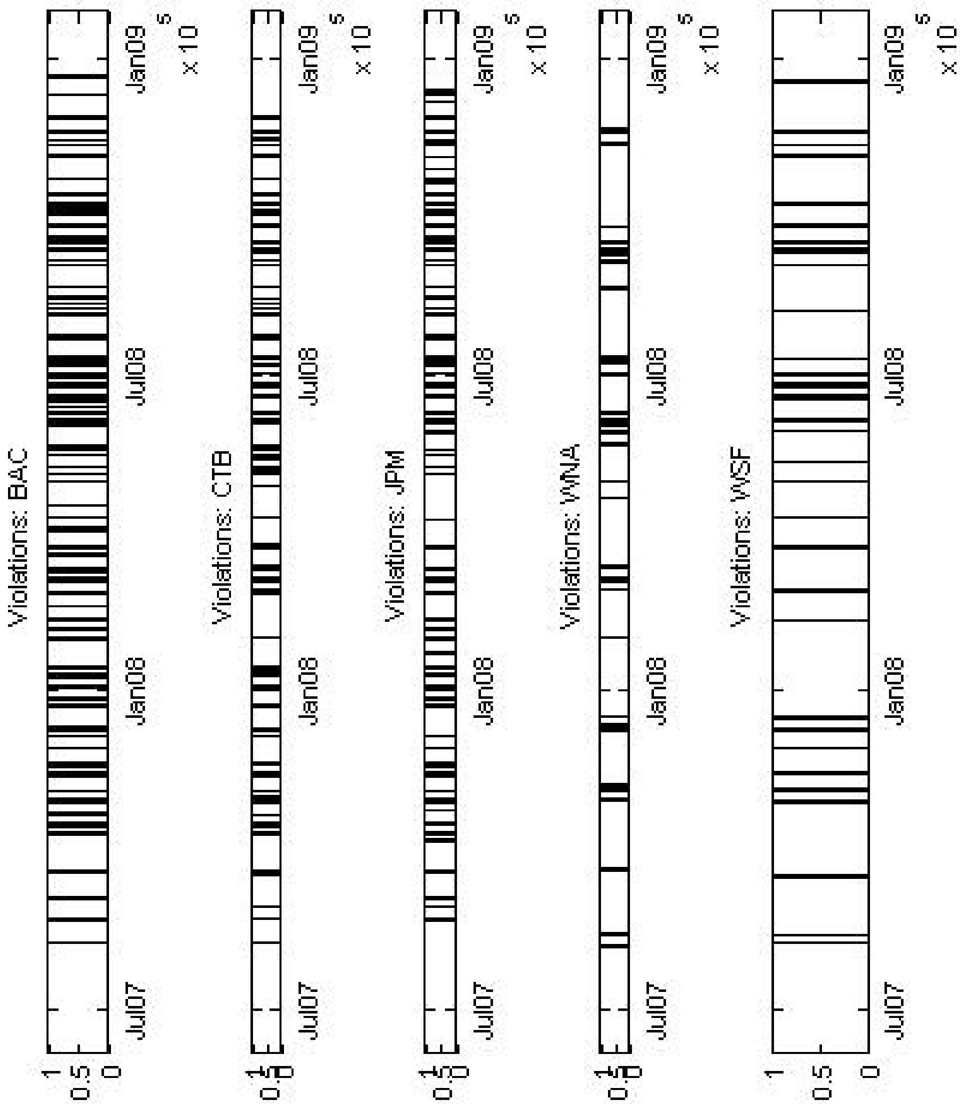

Figure 3: Violation indicator function for univariate *VaR* computed for banks equity returns. Crisis period.

Figure 4: Violation indicator function for univariate *VaR* computed for sector equity returns. Crisis period.

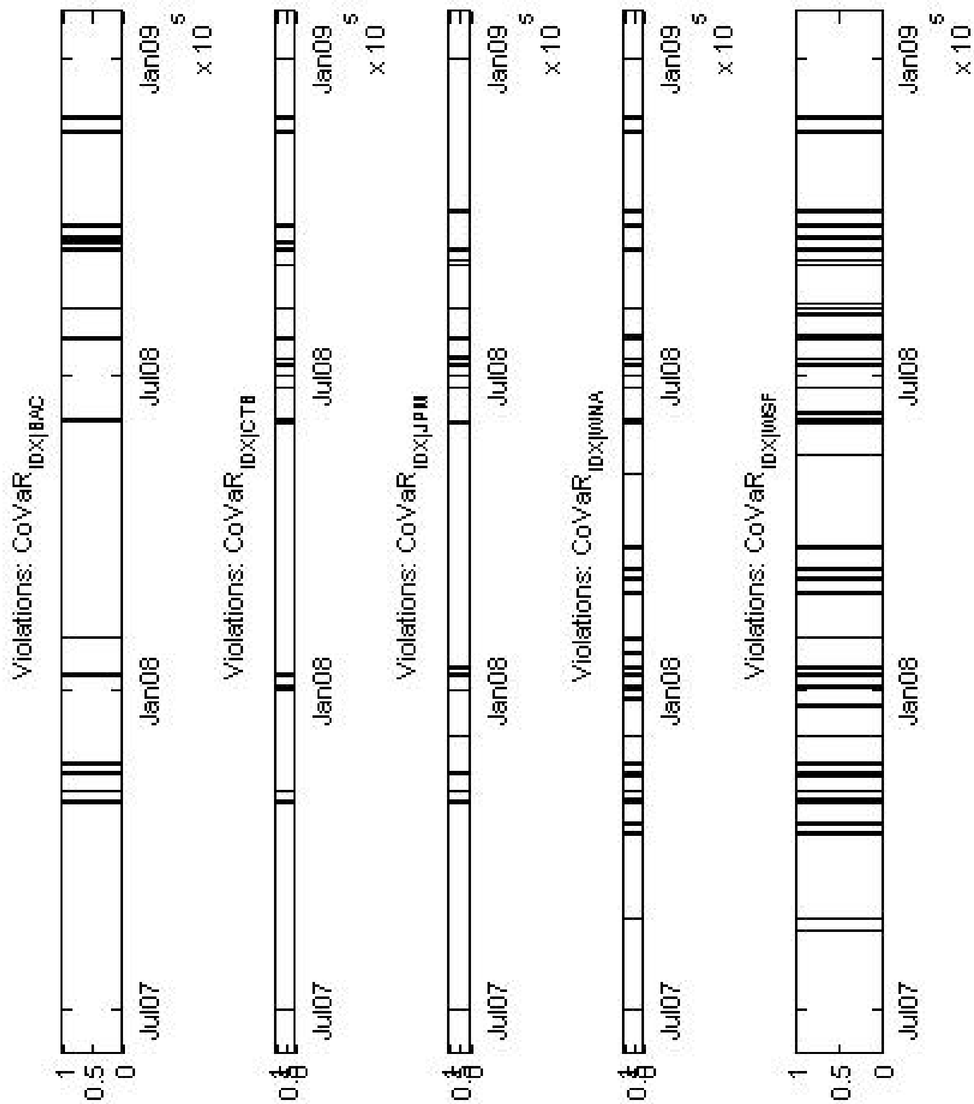

Figure 5: Violation indicator function for univariate *CoVaR* computed for banks equity returns conditional on the indices being below their unconditional *VaR* level. Crisis period.

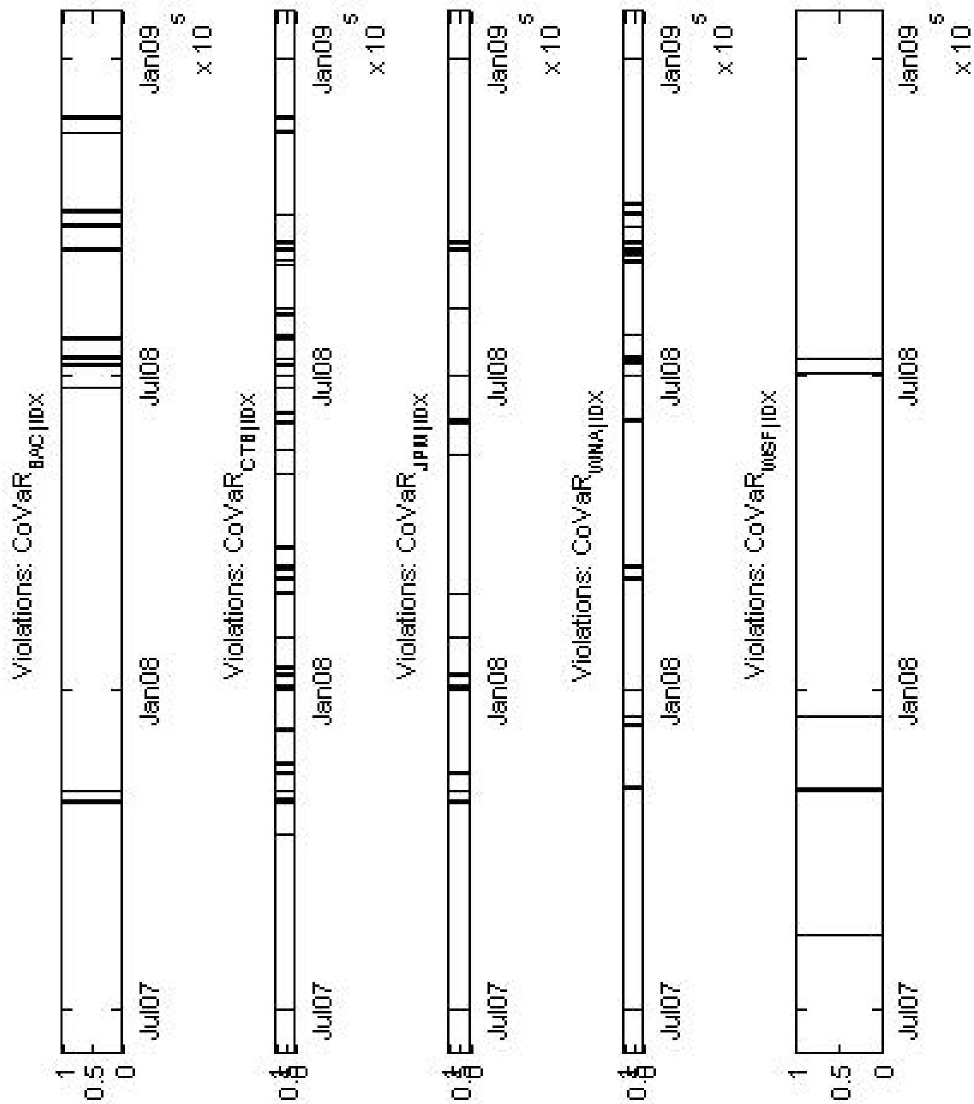

Figure 6: Violation indicator function for univariate *CoVaR* computed for sector equity returns conditional on the banks being below their unconditional *VaR* level. Crisis period.

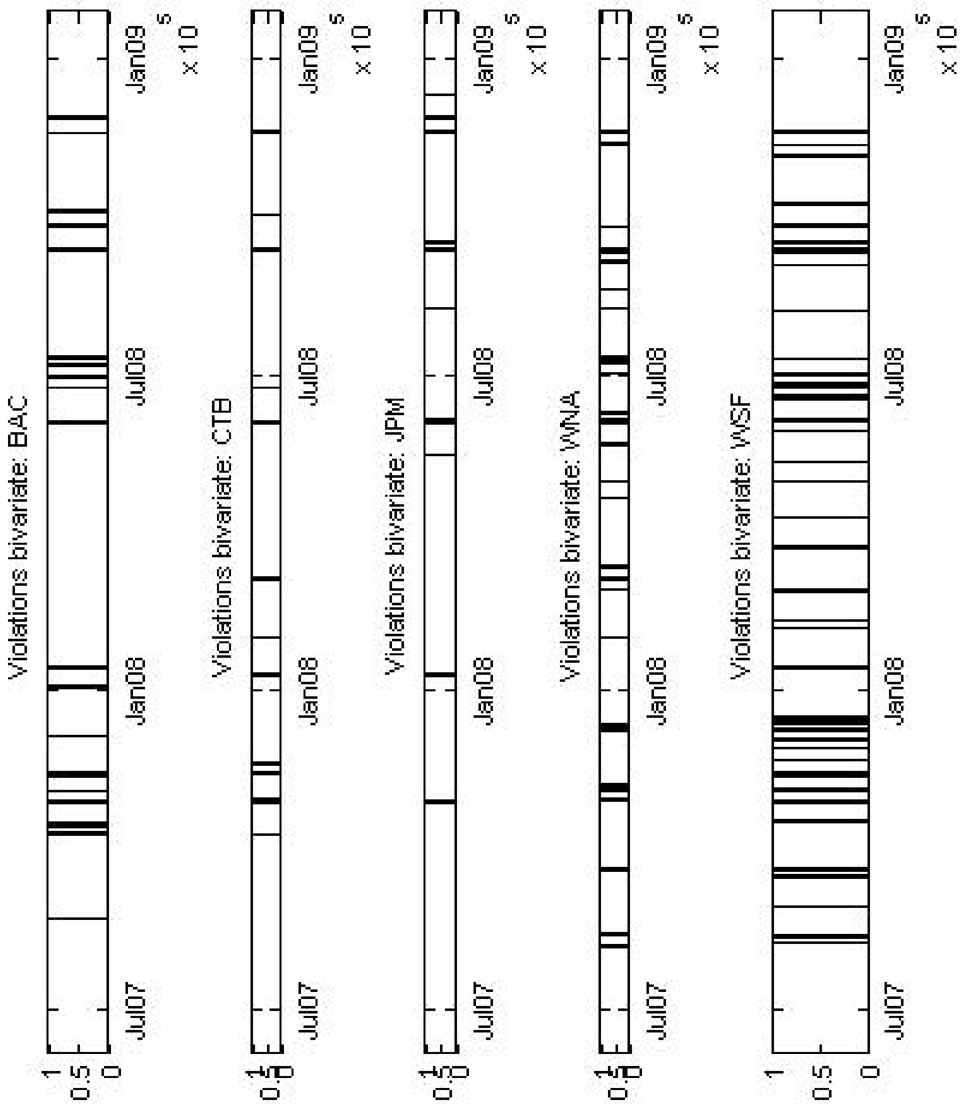

Figure 7: Violation indicator function for bivariate *VaR* computed for banks equity returns. Crisis period.

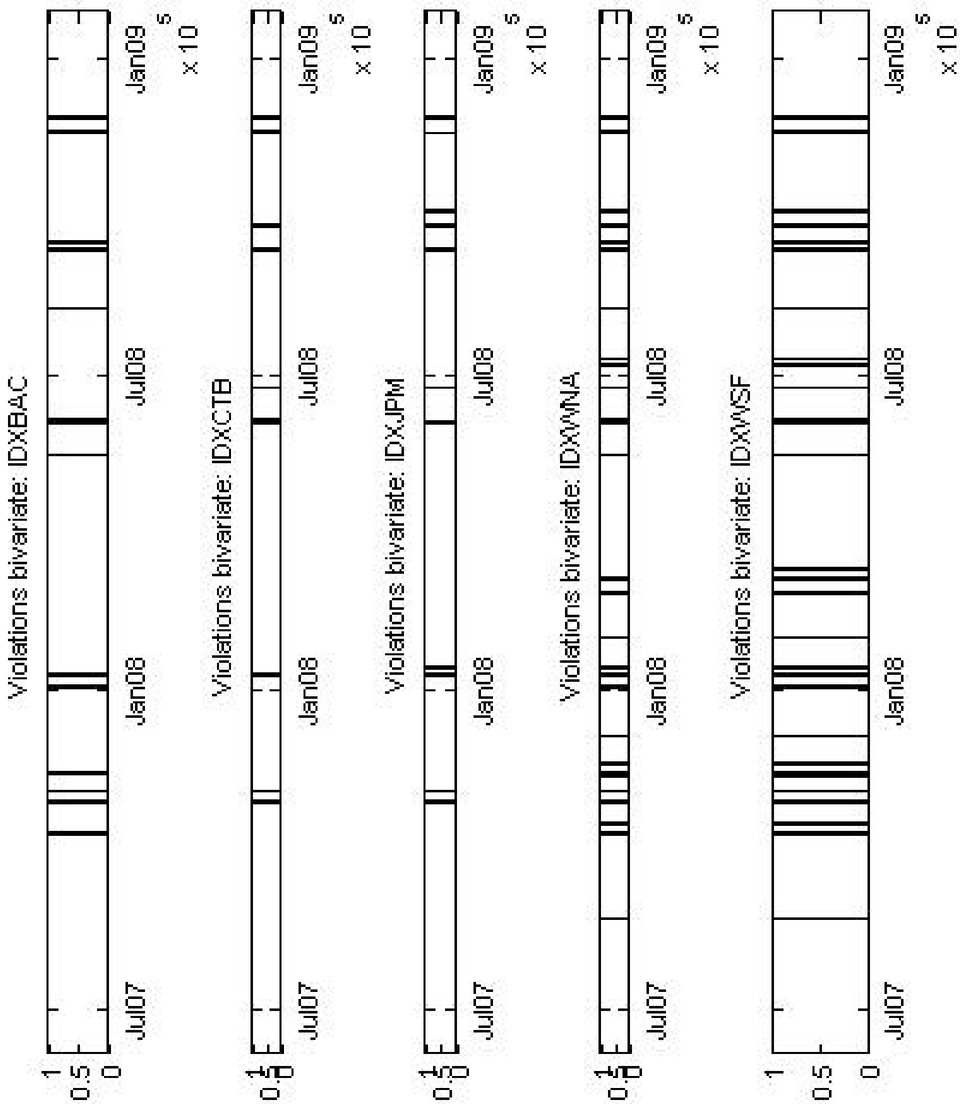

Figure 8: Violation indicator function for bivariate *VaR* computed for sector equity returns. Crisis period.

A Three-Factor GARCH Model for Term Structured Daily Returns

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April 2009

Abstract

This paper proposes a generalized method for the analysis of the conditional variance of term structured series. We estimate a model in which the term structure of financial returns is summarized using three time-varying latent factors - as proposed in Nelson-Siegel (1987) and re-interpreted in Diebold and Li (2000) - which can, in the case of daily returns, display GARCH behavior. Given the substantially different structure that characterizes daily log returns with respect to interest rates along the time dimension, we have to reject the possibility to use in full the specification designed for the analysis of the yield curve confirming the fundamental unpredictability of financial returns. On the other hand, to address the issue of modeling the conditional variance of such series, we augment the model with a GARCH specification showing that there is room for an appreciable reduction of the dimensionality of problems related to conditional variance behavior. In the empirical section we show that this approach allows to handle easily computations - such as volatility impulse response functions- in a multivariate setting; also, the model performs well in terms of out-of-sample forecast of the conditional variance.

Keywords: Term structure; Factor model; Multivariate GARCH; Volatility IRF.

JEL Classification Numbers: C32, C51, G10.

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1 Introduction

The evolution of forward prices curves has been traditionally modeled using stochastic volatility diffusion processes derived from the Black-Scholes-Merton model for option prices. Econometric analysis of such models in continuous time is particularly challenging since the implied conditional density functions involved in the estimation are the solutions to partial differential equations which may be difficult to solve and, moreover, it may be the case that also the asset prices need to be computed numerically as nonlinear functions of the underlying states. One way to cope with these problem is to switch to affine diffusion models, in which the drift and the diffusion coefficient are affine functions of the state process, that yield to more tractable forms (Duffie and Kan (1996), Dai and Singleton (2000)). In the special cases of Gaussian (Cox *et al.* (1985)) or square-root diffusions (Vasicek (1977))), maximum likelihood estimators can be used to derive the key parameters, see At-Sahalia (2001) -(2002), Chen and Scott (1993) and Durham (2001). An alternative strand of literature instead focuses on the estimation of the conditional characteristic function. Using both ML and GMM estimators (among others Singleton (2001)) this approach delivers estimators both in time and frequency domain.

If one restricts the attention to bond pricing only, then there is an extensive literature that has provided a substantially different approach. In particular, yields curves have been suitably explained using parsimonious models in which few factors are able to capture most of the variance of yields at different maturities (Litterman and Acheinkman (1991)). Nelson and Siegel (1987) extract three factors from observed yields which are responsible for most of the overall variance at different maturities and provide a very good in-sample fit. These factors, identified as *level* (long-term factor), *slope* (short-term factor) and *curvature* (medium-term factor) are assumed to follow an AR(1) or VAR(1) process in Diebold and Li (2006), where out-of-sample forecasting performance is also successfully exploited. Recently, Diebol et al. (2006) have shown that these models do not belong to the affine term structure models class, but they still produce reliable estimates and forecast outperforming other models especially at longer horizons.

Besides the evolution of forward prices, the ability to model volatility of asset returns is one of the main feature that characterizes the study of financial series. The importance of such analysis relies in the crucial role played by volatility in most financial models and pricing formulas: asset-pricing models - CAPM among others - show that investors are somehow rewarded for taking risk which is related to the covariance between the market portfolio and the one they hold. On the other hand, option-pricing formulas use volatility of the underlying asset as a fundamental to compute prices of options or other derivatives, and value-at-risk models rely on volatility measures to assess risk in their marketable assets. For a more general market and risk analysis it is often very useful not only to be able to model the evolution of the conditional variance, but also to investigate the effect of shocks on volatility at different maturities. Price changes in the front month contracts affect significantly the whole curve, therefore, it is important to be able to disentangle the consequences of such changes at larger horizons. The transmission of shocks in this setting is usefully modeled via principal component analysis which can efficiently synthesize the driving forces behind a set of forward prices. In a similar fashion, we want to analyze the consequences of shocks on volatility at different maturities which are of high relevance and deserve particular attention.

This paper explores the possibility of constructing a parsimonious model for daily log returns borrowing the theory developed for the term structure of interest rates: provided that forward prices have a term structure similar to the one characterizing interest rates, here we assume that the evolution of the term structure of daily log returns can be explained by the same set of three factors, namely the level, slope and curvature. The choice of such factor decomposition is motivated by Figure (1) below. Here we plot the first three static factors extracted from the data, which together account for more than 90% of the overall variance. The first component is almost constant across all maturities and can be naturally interpreted as a long term component; the second one, starting at 1 and decreasing toward zero as maturity grows, captures short term variations; finally, the third component, which starts at 1 and eventually goes back to the same value, achieves its minimum around maturity equal to 18 months. The strong similarity of such components with the factor loadings associated to the three Nelson and Siegel factors suggests that a potentially powerful tool to describe the term structure of financial returns in a more general setting could be to adapt to this particular case the same idea of parsimonious modeling originally designed for the estimation and forecast of the yield curve.

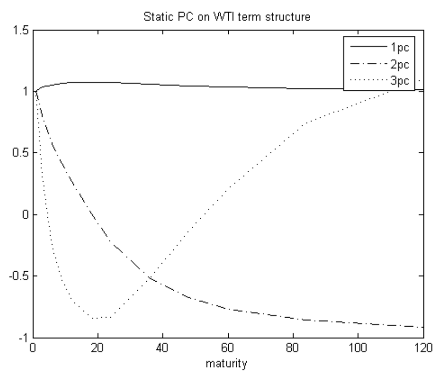

Figure 1: First three principal components extracted from the set of daily returns at fixed maturities.

In the original design, the three dynamic factors follow an unrestricted VAR(1); this process captures the entire dynamic of the term structure and - at the same time - produces a sound out of sample forecast of the yield curve. In the present case, due to the nature of daily log returns, we cannot support the same assumption and therefore produce a forecast for the financial returns. The assumption of a multivariate autoregressive process governing the three factors has been implemented and tested with poor results: the three latent factors display very low mean reverting coefficient which make impossible to exploit forecasting issues in such setting any further.

In order to model the variance of the term structure, the three factors here are assumed to be conditionally heteroskedastic and are thus modeled via a multivariate GARCH specification (Bollerslev (1986)). One interesting feature of assets returns which we want to take into account is the asymmetric way they respond to shocks; empirical research has shown (Black (1976) among others) that returns are negatively correlated with changes in returns volatility - i.e. volatility tends to rise in response to "bad" news (excess returns lower than expected) and to fall in response to "good" ones (excess return higher than expected) leading to what is known as *leverage effect*. This effect was first modeled by Nelson (Nelson (1990)) which introduced the idea of an exponential ARCH model and then further extended to originate a full class of asymmetric GARCH. Among these, we chose to implement a GJR-GARCH (Golsten, Jagannathan and Runkle (1993)) which in its multivariate version extends the asymmetric response to shocks to all innovations in the system and has been successfully employed to verify the presence of spillover effects across different markets.

Provided that we do not intend to model the evolution of a single future, but rather analyze the dynamic governing returns at different, fixed maturities[1], we show that the specification proposed in this paper enables to (I) use a very simple and tractable model to capture returns variations at different time horizons; (II) predict the conditional variance of the whole original term structure and (III) identify different types of shocks and analyze their effect on volatility at different maturities. The specification also provides a tool for returns interpolation and is able to capture the abrupt changes in volatility suffered by most prices in late 2008. Moreover, powerful tools such as volatility impulse response functions can be easily computed due to the important dimensionality reduction imposed by the factor structure.

The remainder of the paper is organized as follows. Section 2 defines the model used throughout the analysis as a GARCH-augmented three factors representation. Section 3 describes the data used and the methodology applied to estimate the model, while results are fully displayed in Section 4. Section 5 concludes.

[1]The analysis is conducted using prices at fixed maturities. Details on the construction of the dataset are provided in section 3 of this paper.

2 The Model

Let $y_{t,t+n}$ be the daily log return of a future contract on a given underlying at time t with fixed maturity $t+n$, and Y_t a vector collecting returns at different maturities so that $Y_t = [y_{t,t+1}, y_{t,t+2}, ..., y_{t,t+k}]'$. The general framework used throughout the analysis can be summarized with the following system:

$$Y_t = X_t \Lambda' + e_t \tag{1}$$

$$X_t = \mu + \phi X_{t-1} + v_t \tag{2}$$

Equations (1) and (2) define a very general setting in which N target variables are assumed to be dependent on a set of r states (with $r < N$) whose dynamic is modeled in equation (2). Equation (1) is the measurement equation in which prices at different maturities are assumed to be determined by a constant term, a set of state variables, and a normally distributed error term ($e_t \; NID(0, \sigma * I)$). The dynamic of the above system is in the state equation - equation (2) - in which the states are assumed to follow an unrestricted VAR(1) process.

The above specified system can be applied to a variety of different settings and in particular, it can be extended to embody situations in which the hypothesis of constant parameters is relaxed, hypothesis that becomes particularly binding especially when dealing with financial series. In this paper in particular we will assume that the states display non constant conditional variance.

We let the conditional variance of X_t display different response to positive and negative shocks; moreover, in a multivariate specification, we also explore the existence of spillover effects across the r underlying states. More formally we model the conditional variance of the stases via a multivariate GJR-GARCH - Golsten, Jagannathan and Runkle (1993) - where:

$$v_t = H_t^{1/2} \eta_t \tag{3}$$

$$H_t = W'W + A' v_{t-1} v_{t-1}' A + G' z_{t-1} z_{t-1}' G + B' H_{t-1} B. \tag{4}$$

where η_t is a sequence of i.i.d. random variables with zero mean and unit variance, $z_{t-1} = v_{t-1} I_{v_{t-1}<0}$, I is an indicator variable, W, A, G and B are matrices of coefficients. The inclusion of z_{t-1} in the above form not only accounts for asymmetry in the conditional variances but also allows for an asymmetric effect in the conditional covariance.

Recall that equation (1) assumes that the term structure is dependent on a set of r state variables. This assumption has been widely used in recent analysis regarding the issue of fitting the yield curve, and several models have been developed according to the particular factor specification. In the most general representation, the states in the measurement equation, whose number is required to be small according to the parsimonious modeling principle, can be endogenous, exogenous, observable or even latent variables.

In the present setting, we test two different specifications of equation (2); in particular, we first consider the case in which variables in X_t are common factors constructed using standard principal component analysis (PCf), then, due to the particular shape of the first three principal components, we also model the latent factors following Nelson and Siegel (1987) (NSf). We show that both specifications produce a consistent estimate of the overall shape of the term structure, however, due to significantly more accurate in-sample fit, NSf are preferred to carry the estimation and forecast of the conditional variance.

3 Data and Econometric Methodology

We apply the model described in the previous section to a data set containing daily quotations of WTI (West Texas Intermediate) Crude Oil futures contracts at different maturities spanning the period which goes from 06-Jan-2005 to 31-Dec-2008 and are drawn from the Calyon CIB London / FAME Database. WTI contracts are subject to monthly expiry. In order to avoid the inclusion of time to maturity in the present analysis, we implement a monthly rolling window system which transforms data into prices at fixed maturity. The idea is explained in Table (1).

Table 1: Construction of the dataset

time	contract			
m $m-1$ $m-2$ $\vdots$ $m-n$	contract expiring in month $m+1$: c_{m+1}	contract expiring in month $m+2$: c_{m+2}	$\cdots$	contract expiring in month $m+k$: c_{m+k}

time	fixed maturity			
m	c_{m+1}	c_{m+2}	$\cdots$	c_{m+k}
$m-1$	c_m	c_{m+1}	$\cdots$	c_{m+k-1}
$m-2$	c_{m-1}	c_m	$\cdots$	c_{m+k-2}
$\vdots$	$\vdots$	$\vdots$		$\vdots$
$m-n$	c_{m+1-n}	c_{m+2-n}	$\cdots$	c_{m+k-n}

In panel 1 (top) the original data describing the evolution of contracts over time. In panel 2 the transformation adopted to obtain data at fixed maturity: on a monthly basis, with time decreasing, the panel is rolled backward so that elements in each column share the same time to maturity.

The first panel depicts the original data. At each point in time several contracts are available, each of them with its own expiry. Clearly, as we move forward in time the composition of the panel will change with new contracts taking the place of those already expired. Given that we are not interested in the evolution of a specific contract, but rather in the dynamic governing prices at different maturity, we roll backward contracts on a monthly basis in order to obtain the composition described in the second panel of Table (1) where data in each column share the same time to maturity. Such data constitute the basis of our analysis; in particular we select 13 different fixed maturities, namely 1m, 2m, 3m, 6m, 9m, 1y, 1.5y, 2y, 3y, 4y, 5y, 7y, 10y with a total of 1030 observations per maturity.

In order to exploit out of sample properties of the proposed model the estimation is carried over data up to beginning of June 2008 whereas the last 150 trading days are left out for forecasting. Daily log returns computed using this set of data are plotted in figure 2 below.

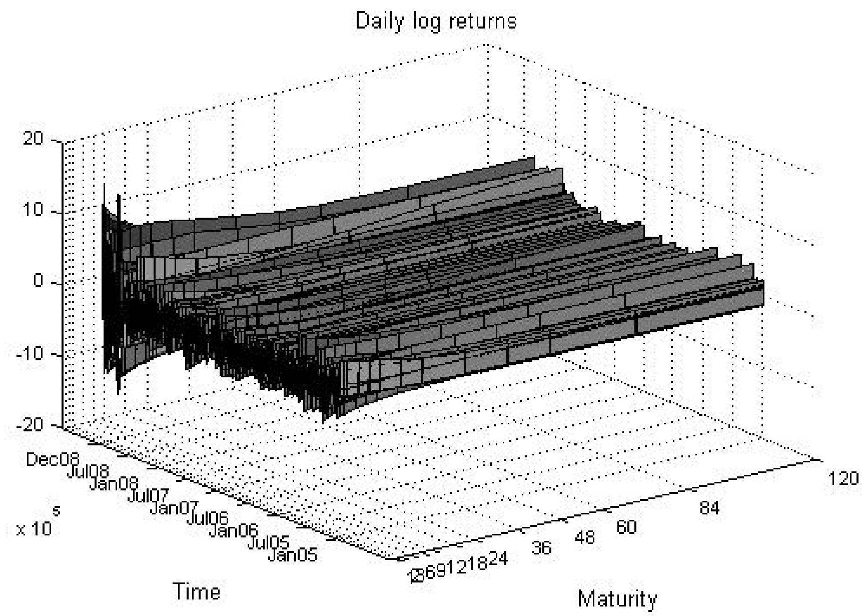

Figure 2: Daily log returns for WTI Crude Oil contracts from 6.01.2005 to 31.12.2008. Contracts are evaluated at 13 fixed maturities in between 1 month and 10 years

The peculiarity of the data, and the main difference between the yield curve and the set of daily log returns analyzed here, concentrates mainly on the time dimension as clearly visible from Figure (2). As expected, daily returns tend to display very small persistence as they rather oscillate around the mean. This particular feature implies that specifications which model the dynamic according to autoregressive processes - like the one proposed here - will perform extremely poorly in terms of returns forecast. Taking this into account, we will concentrate solely on the dimensionality reduction problem (i.e. find the best set of factors to capture the evolution of the term structure) and on the analysis of the conditional variance of the returns. Prices included in the set of data clearly belong to contracts whit very different liquidity, nonetheless, the introduction of data up to maturity y10 is motivated by the fact that we want to stress the idea that a very small set of signals can produce sound estimation of the term structure even for far maturities. All results are robust to a reduction of the dataset in terms of maturity considered.

In order to test the appropriateness of the factor specification, we begin with the estimation of the term structure using two different variations of equation (1) which read as follows:

$$Y = PCf\Lambda' + e_{PCf} \tag{5}$$

$$Y = NSf\Lambda' + e_{NSf} \tag{6}$$

In the first variation the factors are computed using standard principal component analysis, then, given the shape depicted in Figure (1), the second variation explicitly models the factor to identify a long, short and medium term component. More formally,according to equation (5) the target variable depends on a set of static factors which are computed as

$$PCf = Y'\hat{\Lambda}/N \tag{7}$$

where $\hat{\Lambda}$ is the solution of the principal component problem of maximizing the trace of $(\Lambda' Y' Y \Lambda)$ subject to $\Lambda'\Lambda/N = I_r$ and N is the number of maturities in the sample. The number of factor is set to be equal to three for direct comparison with the Nelson and Siegel approach. Equation (6) on the other hand assumes that

$$\Lambda' = [1, (\frac{1 - e^{-\lambda n}}{\lambda n}), -(\frac{1 - e^{-\lambda n}}{\lambda n} - e^{-\lambda n})] \tag{8}$$

where $n = 1 \ldots N$ and λ λ determines the exponential decay rate. The larger λ, the faster the rate of decay, the better the fit at short maturities. Furthermore, λ also determines when the coefficient associated to the third factor achieves its maximum. In this context, the three factors associated to the above defined factor loadings are identified with the *level* (L_t), the *slope* (S_t) and the *curvature* (C_t) of the term structure itself. The estimation of NSf is carried over subsequent steps which start with the identification of λ as the coefficient that maximizes the curvature loading at medium-term maturities. We set the medium-term maturity equal to 18 months and therefore fix $\lambda = 0.096$. Once the loadings are computed, the three latent factors are estimated applying OLS to the cross-section of returns at different maturities where the loadings are treated as fixed regressors. Table (2) below summarizes the characteristics of the two sets of factors.

PCf have zero mean and unit variance by construction and tend to display excess kurtosis. The Level is - on average - the only positive factor, while most of the variability depends on the Curvature. All three factors are negatively skewed and have a higher kurtosis with respect to the Gaussian distribution. Likewise, the Kolmogorov-Smirnov and the Jarque-Bera test for normality generally reject the null at a 5% level. LM test results for the presence of squared autocorrelation indicate very significant second moment dependencies in both cases justifying the GARCH specification to model the conditional variance. Since in this particular exercise we are not interested in obtaining density forecast (Diebold, Gunther and Tay (1998)) or in examining VaR estimates (Rombouts and Verbeek (2004)) for which a more accurate distribution of the innovation is desirable, multivariate GJR-GARCH employed here is estimated maximizing a Gaussian likelihood function. The normality assumption is justified by the fact that QML estimator is consistent under some regularity conditions (Bollerslev and Wooldridge (1992)).

4 Empirical Findings

4.1 In-sample fit and model selection

One of the peculiarities of the daily log returns is that - over the time dimension - it is very hard, if possible, to find a process that depending on past information would give back enough structure to produce reliable out-of sample fit of the term structure. In other words, if can safely assume that the term structure can be explained through a small number of factors, then prediction of the term structure is feasible only if the VAR process modeling the dynamic in the state equation -

Table 2: Summary statistics

	PCf			NSf		
	Factor 1	Factor 2	Factor 3	Level	Slope	Curvature
Sample Mean	0.0000	0.0000	0.0000	0.0945	-0.0137	-0.0454
Variance	1.0000	1.0000	1.0000	1.7145	1.292	2.9313
Skewness	-0.0036	0.1108	-1.9203	-0.0874	-0.1272	-0.84
Kurtosis	3.2132	4.4354	22.8123	3.5515	4.9298	8.0735
Min	-3.3042	-5.0491	-9.465	-4.7439	-5.8906	-10.4318
Max	3.7748	3.5873	5.8826	5.0944	3.8958	7.8168
KS	0.0224	0.0379	0.0859	0.0821	0.0307	0.0954
	(0.7641)	(0.1551)	(0.0000)	(0.0002)	(0.5297)	(0.0000)
JB	1.6662	77.2618	14916.48	9.5683	108.2998	816.4081
	(0.4347)	(0.0000)	(0.0000)	(0.0084)	(0.0000)	(0.0000)
$LM(y^2, 5)$	14.4551	32.5922	103.5678	8.2976	11.8612	84.8818
	(0.0001)	(0.0006)	(0.0000)	(0.004)	(0.0006)	(0.0000)
	18.1025	66.1986	172.1118	25.7585	14.2793	116.3908
	(0.0001)	(0.0008)	(0.0000)	(0.0000)	(0.0008)	(0.0000)
	18.1781	69.4923	200.2454	26.355	69.9817	118.4237
	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	19.0245	71.025	201.0195	37.7758	70.6998	121.9538
	(0.0008)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	25.3511	71.4088	200.9226	38.7664	70.7927	124.4222
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Sample period is 6-Jan-2005 to 6-Jun-2008.

KS and JB are the Kolmogorov-Smirnov and Jarque-Bera test for normality.

$LM(y^2, 5)$ is the LM test for the squared factors. P-values in parentheses

Table 3: Persistency check on extracted factors

VAR(1) for PCf			
	$F1_t$	$F2_t$	$F3_t$
ϕ	0.0022	-0.0031	-0.0017
	(-0.03349)	(-0.0319)	(-0.03212)
$F1_{t-1}$	-0.0679	0.0308	-0.0980
	(-0.03352)	(-0.03193)	(-0.03215)
$F2_{t-1}$	0.0911	0.3065	0.0531
	(-0.03349)	(-0.0319)	(-0.03213)
$F3_{t-1}$	-0.0049	-0.0638	0.2851
	(-0.03349)	(-0.0319)	(-0.03212)

VAR(1) for NSf			
	L_t	S_t	C_t
ϕ	0.133091	-0.00517	-0.02718
	(-0.04295)	(-0.04204)	(-0.04117)
L_{t-1}	0.023618	-0.15778	0.119275
	(-0.03424)	(-0.03351)	(-0.03282)
S_{t-1}	-0.22493	0.184217	0.124624
	(-0.03381)	(-0.0331)	(-0.03241)
C_{t-1}	-0.01319	-0.08786	0.31225
	(-0.03554)	(-0.03479)	(-0.03407)

Dynamic of the two sets of states. In the first panel (top) the results refer to an unrestricted VAR(1) on the latent factors estimated via principal components analysis; in panel b the same estimation is performed on factors estimated from Nelson-Siegel loadings. Standard errors in parentheses.

equation (2) - is able to capture the evolution of such factors or, equivalently, if the series in X_t display strong persistency.

Obviously, unlike the yield curve case, when applying such forms of parsimonious modeling to financial returns in a more broad definition, we find (Table 3) that the three factors (both PCf and NSf) display small - if significant - autoregressive coefficients confirming the substantial unpredictability of financial returns. Therefore, we do not exploit the out-of-sample performance of such model in this

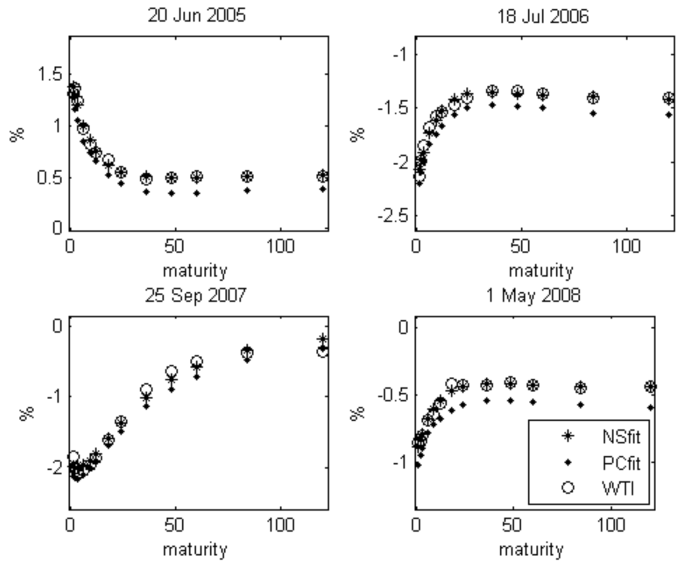

Figure 3: Examples of goodness of fit provided by the two specifications PCf and NSf, RMSE for the four selected dates are 0.1345, 0.1303, 0.1601, 0.1306, for PCf and 0.0371, 0.0372, 0.0943, 0.0238, for NSf respectively

setting focusing entirely on volatility modeling rather than returns prediction.

In order to select the best specification to carry the estimation and forecast of the conditional variance, we check the accuracy of the in-sample fit of the term structure provided by the two specifications. It emerges that both sets of factors can reproduce the overall shape of the term structure, however, NSf factors are far more accurate with RMSE lying substantially below the ones computed using computed PCf. A graphical example of the goodness-of-fit induced by the NS model is in Figure 3. Here the comparison between the true values and the two estimated ones are plotted for four dates extracted from the sample time span. In particular PCf, while correctly capturing the evolution of the returns across the maturity dimension, tend to underestimate the structure.

An important byproduct of the proposed model is returns interpolation. In the present case we obtain that explaining daily log returns as a combination of level, slope and curvature components allows to fit quite accurately a curve counting 13 different maturities using as little as three factors. Such a result suggests that this simple and lowly computationally demanding parsimonious framework constitutes a powerful tool to derive the value of returns at maturities which might not be available in the original data composition.

4.2 Variance forecast

In the previous sections we have shown that the structure identified by the Nelson and Siegel level, slope and curvature designed for the analysis of the yield curve also allows to capture accurately the term structure that characterizes financial returns in a more general setting. In this section we employ the reduction of dimensionality imposed by the factor structure to analyze the variation that financial markets experienced towards the end of 2008. We will show that the parsimonious framework allows to recover consistently the conditional variance of all the series in the sample, also, provided that it is possible to construct level, slope and curvature variances, we can also analyze the effect that shocks have on the variance at different maturities.

Recall from section (2) that the conditional variance of the states is modeled according to a multivariate GJR-GARCH in order to capture both asymmetries and possible spillover effects. Parameter estimates of the GJR model are obtained by maximizing the log-likelihood function with conditional log-likelihood functions computed as $L_t(\theta) = -\log 2\Pi - 0.5 \log |H_t| - 0.5 e_t'(\theta) H_{t-1}(\theta) e_t'(\theta)$ where θ is the vector of all parameters of the model. In the multivariate version, the estimation of the GJR model produces three matrices of interest which capture the effect of the lagged variance (matrix B), the lagged returns (A) and the lagged negative returns (G) on the conditional variance of the states.

In the estimation of the long term, short term and medium term variances the coefficients reported in matrix G confirm the presence of the leverage effect for the returns included in the sample; the elements on the main diagonal are all positive and strongly significant highlighting the larger impact that negative changes in the states have on their own conditional variance. On the other hand, significant and mostly negative off diagonal elements suggest that there is interaction between the states and that negative changes in one of the states returns tend to decrease the variance of the remaining states. Spillover effects are also pointed out from the results of the estimation of matrices A and B. In general the variance of each of the states increases after a change in the lagged own returns, with the effect being more intense in presence of negative returns. The cross effects are mainly negative, i.e. a negative return in the long term component will cause the long term variance to increase but, at the same time, will reduce the short term variance by a small but yet significant amount; the leverage effect therefore, is reduced by the presence of spillovers between the three components. Estimation results are in table (4) below.

Table 4: Estimated coefficients for MGJR-GARCH

	Level		Slope		Curvature
a_{11}	0.0414	a_{12}	-0.0795	a_{13}	0.0353
	(0.0019)		(0.0019)		(0.0073)
a_{21}	-0.0372	a_{22}	-0.002	a_{23}	0.0043
	(0.0054)		(0.0008)		(0.0083)
a_{31}	-0.0176	a_{32}	-0.0743	a_{33}	0.0109
	(0.007)		(0.0001)		(0.0027)
g_{11}	0.2249	g_{12}	-0.0272	g_{13}	-0.0191
	(0.0464)		(0.0087)		(0.0228)
g_{21}	-0.0133	g_{22}	0.2456	g_{23}	-0.0158
	(0.0053)		(0.0115)		(0.015)
g_{31}	-0.0981	g_{32}	-0.0608	g_{33}	0.2139
	(0.0191)		(0.0509)		(0.0314)
b_{11}	0.6779	b_{12}	-0.0486	b_{13}	0.0322
	(0.0117)		(0.0058)		(0.0106)
b_{21}	-0.0355	b_{22}	0.6884	b_{23}	-0.0014
	(0.02)		(0.0329)		(0.0084)
b_{31}	-0.1775	b_{32}	-0.1448	b_{33}	0.6867
	(0.0396)		(0.054)		(0.0069)

Standard errors in parentheses.

Once the conditional variance of the latent factor is estimated, it is possible, from the parsimonious representation to go back to the full model and check that the model presented here is able to forecast the evolution not only of the the 1 day ahead factors variance, but of the term structure as a whole. We achieve this through equation (1) assuming that the conditional variance of e_t is constant over time and equal to its unconditional level. 95% confidence intervals for some of the series in Y_t are shown in Figure 4. The reference period covers the last 250 trading days, of these the last 150 were left out of the estimation process.

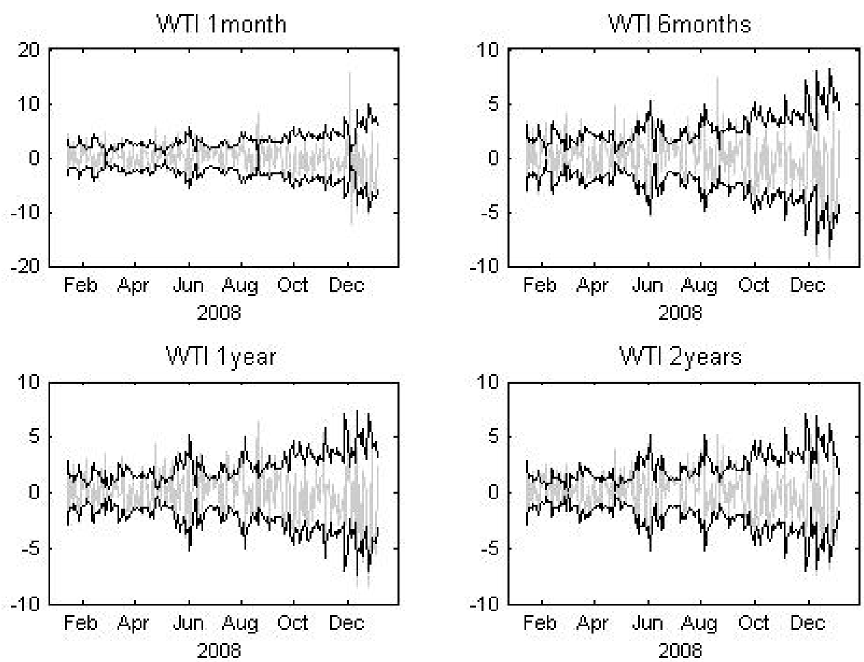

Figure 4: 95% confidence intervals for WTI returns over the last 250 trading days in the sample time span. The last 150 days were not included in the estimation process.

The picture shows 95% confidence intervals computed from the forecasted 1 day ahead conditional variance of the term structure as a function of the 1 day ahead conditional variance of the states. Assuming that the heteroskedasticity in the original data is fully captured by the conditional variance of the states and even though the parameters of the model are estimated during a relatively calm period, the proposed specification makes it possible to analyze the abrupt variation of prices occurred in the last few months of 2008; the idea of decomposing the returns term structure into level, slope and curvature, allows not only to estimate the term structure itself, but can successfully be employed as a tool for variance forecasting even in the presence of periods of financial turmoils.

One more feature of the proposed specification relies in the possibility of analyzing the effect that shocks at different maturities have on the variance of the states, and thus on the variance of the whole term structure. The presence of asymmetric responses is exploited via two different tools, namely, the multivariate extension of the News Impact Curves (Engle and Ng (1993)) and the construction of Generalized Impulse Response Functions (Koop *et al.* (1996)).

News Impact Surfaces measure the relation existing between the conditional variance and lagged squared returns when lagged variance is set to be equal to the unconditional value. In order to compute such curves at each time we let one of the three factor to have value zero. Results are in Figure 5. All computed variances - except the one for the slope - respond asymmetrically both to own and other squared lagged returns with the difference in the effect being captured by the estimated coefficients of the GJR model. In particular, as expected, the short term variance seems to react only in presence of negative shocks happening at short maturities, whereas positive and negative changes in the short term propagates both the long term and medium term variance of the structure (panel (c) and (d) of figure 5).

Another interesting tool which is made computationally feasible due to the important reduction of dimensionality - from 13 maturities to 3 factors - is the construction of variance impulse response functions. In order to compute such responses, we follow the approach defined by Koop *et al.* and generate Generalized Impulse Response Functions (GIRF) to check which kind of effect, if any, is pro-

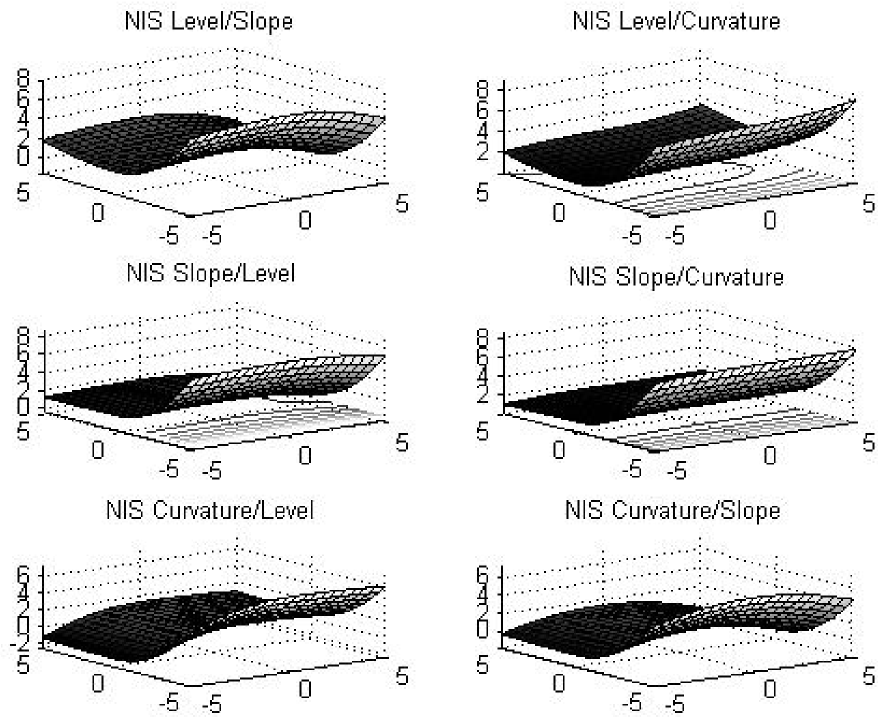

Figure 5: News Impact Surfaces measuring the relation that exists between the conditional variance and lagged square returns when lagged variance is set to be equal to its unconditional value.

duced by positive and negative shocks. For an arbitrary shock $\nu_t = \delta$ and history Ω_{t-1}, the GIRF is defined as

$$GIRF = E[H_{T+h}|\nu_t = \delta, \Omega_{t-1}] - E[H_{T+h}|\Omega_{t-1}] \tag{9}$$

Responses due to negative and positive shocks, whose shape is suggested by the coefficients of the multivariate GJR-GARCH, are plotted in Figure 6 and Figure 7.

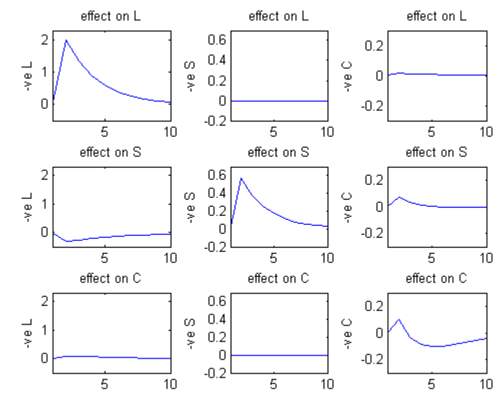

Figure 6: Generalized volatility impulse response function as effect of a negative one standard deviation shock

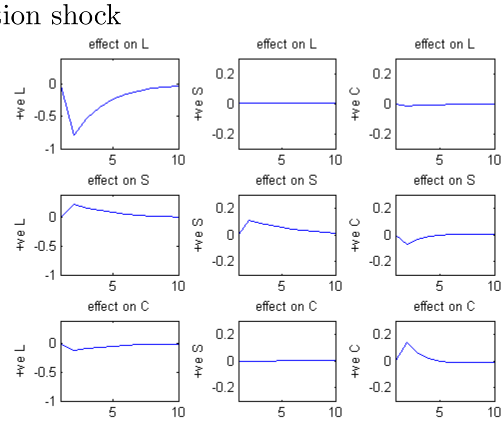

Figure 7: Generalized volatility impulse response function as effect of a positive one standard deviation shock

5 Conclusion

This paper proposes the use of the three factors designed for the estimation and forecast of the term structure of interest rate to generate reliable forecast of the conditional variance of term structured daily financial returns in general.

These factors, whose variance is modeled via a multivariate GJR-GARCH allow to construct sensible tools to analyze the effect that large positive and negative returns have on the overall variation of the structure itself using a reduced number of variables which make the computation of News Impact Surfaces and Generalized Volatility Impulse Response Function more tractable even when dealing with a large number of original series. Moreover, such specification produces sufficiently accurate forecast of the one period ahead conditional variance of the term structure even in presence of periods of financial turmoils allowing to capture the major changes experienced by financial markets during the second half of 2008.

The empirical exercise, conducted on a panel covering about three years of daily log returns for Oil contracts at different maturities, shows that such a parsimonious framework is a simple and easy to implement tool to analyze the term structure of daily returns and their variation over time. Particularly, out-of-sample forecasts of the variance of the whole panel is easily computed providing important tools for risk analysis.

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Business Cycle Forecasts and Stock Market Fluctuations: How Much does the Stock Market Price?

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September 2007

Abstract

This paper argues that different perceptions on the same economic variable are priced-in into the stock market. In particular, defining as the excess optimism the difference in perception between the financial and the macroeconomic sectors, we show that such difference constitutes a significant predictor of stock market returns. The results suggest that the market perceives the optimism of the financial sector as a source of instability and thus tends to resize the effect when this happens at short to medium horizon; on the other hand, if the effect is persistent, it is interpreted as a positive piece of information which boosts the growth rate of stock market returns in the long term.

Keywords: Dynamic Factor Model; Large panel; Interaction between macroeconomic and financial variables.

JEL Classification Numbers: G17, C32

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1 Introduction

The existence of a relationship between macroeconomic variables and the stock markets is now recognized and has been widely analyzed both in its short-run and long-run components. The empirical evidence suggests that stock prices tend to react to macroeconomic fluctuations and this phenomenon is supported by a large number of studies which on one hand exploit the explanatory power that macroeconomic variables have on the stock returns and, on the other hand verify the existence of long-run relationship between the driving forces of the stock market and aggregate economic variables.

At a short-run level the work by Fama (1981, 1990), Chen *et al* (1986), Barro (1990) and Cheung *et al* (1997a, 1997b) among others, shows that international market data support the existence of a degree of correlation between the stock market and the real aggregates. The nature of such short-run relationships has been incorporated in a wider framework where such movements are interpreted as deviations from long-run equilibria by Cheung *et al* (1998) among others. In their analysis the long-run cointegrating relationship is added to the specification proposed by Fama (1990) to improve the model for stock returns.

In this paper we assert that despite the dependence between the stock market and economic aggregates, financial and macroeconomic variables respond to different but yet equivalently important sets of information. If this is true then the same set of variables will be perceived differently if we look at it from a financial or a macroeconomic perspective; moreover, it is possible to construct excess optimism variables which capture such difference in perception. We argue that stock market fluctuations price-in such difference in perception at different time horizons showing that quarterly growth rates of excess optimism variables constructed for inflation and income are significant predictors of quarterly growth rates of stock market returns at different horizons.

In order to capture the information embedded into what we refer to as the macroeconomic and financial perspectives we employ generalized dynamic factor models as in Forni *et al* (2005) to extract signals from two large macroeconomic and financial panels of US data. The attractiveness of dynamic factor models has been analyzed in several studies where time series variables are defined as the sum of a common and idiosyncratic component which are mutually orthogonal. In particular, the information carried in large panels of data is successfully captures by the common component which can be estimated using different approaches.

The method proposed in Stock and Watson (2002) estimates the common component projecting onto the static principal components of the data. This method, which provides useful tools for forecasting purposes, considers only contemporaneous information failing to capture the lagging-leading relations between the variables in the data set. The more recent approach suggested by Forni *et al* (2005) combines the usefulness of having leads and lags considered in the analysis with the need of producing reliable out-of-sample forecast in a two step procedure. The method, which we use in this paper, recovers first the estimates of the common and idiosyncratic covariance matrices at all leads and lags and then the relevant contemporaneous relations are recovered as the result of a generalized principal component problem.

The remainder of the paper is organized as follows: section 2 defines the theoretical framework and the estimation procedure, data and results are discussed in section 3 while section 4 concludes. A complete list of data used and transformations applied are reported in the Appendix.

2 Model Specification

It is well known that stock market prices react to changes in the real economy, in particular, it has been argued (Fisher and Merton (1985) among others) that the stock market behaves as a good predictor of the business cycle. In this setting what we are interested in is whether the stock market prices the different perception that two separate information set can produce on the same variable. In order to do so we develop a two step procedure which allows first to identify and extract the relevant information carried within a given set of data, second to exploit how much this difference is significant in terms of stock market returns prediction.

In a first step we consider two panels of data which contain macroeconomic and financial variables respectively, and define them as being the sum of a common and idiosyncratic component; then we recover the two common components and use them to predict quarterly growth rates of economic variables at different horizons: these sets of predictions will then be used to construct a distance variable, which we call excess optimism, that will in turn be used as a predictor for the quarterly growth rate of stock market returns at different horizons.

2.1 Different perceptions: signal extraction

The first step in this analysis is to identify the way the financial and the real markets predict a given economic variable.
As widely discussed in Forni *et al.* (2000, 2005), Giannone *et al.* (2002), if x_{it} is a collection of variables, under suitable conditions, namely, if there is high collinearity, then it is safe to assume that x_{it} follows a dynamic factor model and can thus be represented as

$$x_{nt} = \chi_{nt} + \xi_{nt} \tag{1}$$

where

$$\chi_{nt} = b_n(L)u_t = \sum_{h=1}^{q} b_{nh}(L)u_{ht}$$

is the *common component*, $u_t = (u_{1t}, ..., u_{qt})'$ is a q-dimensional vector of common shocks which are unit variance white noise orthogonal at all leads and lags, $b_n(L)$ is a row vector of infinite order polynomials in the lag operator and ξ_{nt} is the *idiosyncratic component* orthogonal to the common shocks.

The advantage of expressing the information carried by a large set of variables using few indices only, is clearly that of reducing considerably the dimensionality of the problem one deals with. In this specific setting, this will allow to construct the 'feeling' that each of the considered environments exhibits with respect to a given event as it is synthesized into the common shocks themselves. Therefore, in order to extract the information provided by the financial and macroeconomic variables, the panel is accordingly split into two partitions to allow for the identification of the common shocks driving each of the two markets separately.

Denote by $\Sigma_n^T(\omega)$, with $\omega = [-\pi, \pi]$ a consistent estimator of the spectral density $\Sigma_n(\omega)$ of x_{it}. Let $\lambda_{nj}^T(\omega)$ be $\Sigma_n^T(\omega)$'s j-th largest eigenvalues and $\mathbf{p}_{nj}^T(\omega) = (p_{nj,1}^T(\omega), \ldots, (p_{nj,n}^T(\omega))$ the corresponding row eigenvector. The estimators for the spectral density matrices of χ_{nt} and ξ_{nt} are respectively

$$\Sigma_n^{\chi T}(\omega) = \lambda_{i1}^T(\omega)\tilde{\mathbf{p}}_{n1}^T(\omega)\mathbf{p}_{n1}^T(\omega) + \ldots + \lambda_{i1}^T(\omega)\tilde{\mathbf{p}}_{nq}^T(\omega)\mathbf{p}_{nq}^T(\omega) \tag{2}$$

$$\Sigma_n^{\xi T}(\omega) = \lambda_{n,q+1}^T(\omega)\tilde{\mathbf{p}}_{n,q+1}^T(\omega)\mathbf{p}_{n,q+1}^T(\omega) + \ldots + \lambda_{nn}^T(\omega)\tilde{\mathbf{p}}_{nn}^T(\omega)\mathbf{p}_{nn}^T(\omega) \tag{3}$$

where the tilde denotes transpose and conjugate; and the estimates of the k-lag covariance matrices of χ_{it} and ξ_{it} are respectively

$$\Gamma_{nk}^{\chi T} = \int_{-\pi}^{\pi} \exp(ik\omega)\Sigma_n^{\chi T}(\omega)d\omega \tag{4}$$

$$\Gamma_{nk}^{\xi T} = \int_{-\pi}^{\pi} \exp(ik\omega)\Sigma_n^{\xi T}(\omega)d\omega \tag{5}$$

The estimates of the covariance matrices of the common and idiosyncratic components obtained with the dynamic procedure are then used to recover r linear combinations of the original data set solving a *generalized eigenvalue problem.* More precisely, the common shocks will be the *generalized eigenvectors* ($v_{ij}^T, j = 1, \ldots, r$) associated to the r largest *generalized eigenvalues* ν_{nj}^T of the couple of matrices $(\Gamma_{n0}^{\chi T}, \Gamma_{n0}^{\xi T})$, that is

$$v_{nj}^T \Gamma_{n0}^{\chi T} = \nu_{nj}^T \Gamma_{n0}^{\chi T} \Gamma_{n0}^{\xi T}. \tag{6}$$

2.2 Recovering the effect on the Asset Returns

Once the signals are identified, they are then directly used to construct the different perceptions the two markets have on the same economic variable. Table 1 below summarizes the share of variance explained by the first 5 dynamic principal components at all frequencies [1] whereas Figure 1 and 2 report the extracted components. Results are computed in percentage of the total variance and each row reports the marginal contribution of each of the dynamic eigenvalues. According to the share of explained variance we choose to keep 4 and 3 components for the macroeconomic and financial partition respectively, the selected components together count for about the 80% of the total variance of each respective panel.

Table 1: Share of variance explained by the first 5 DPC

DPC	macroeconomic partition	financial partition
1	0.4834	0.4078
2	0.6335	0.6791
3	0.7163	0.7955
4	0.8076	0.8678
5	0.8587	0.9193

Let $F_t = (F_{1,t}, \ldots, F_{r,t})'$ and $M_t = (M_{1,t}, \ldots, M_{r,t})'$ collect the components extracted from the financial and the macroeconomic set respectively, then the perception provided by the two will be constructed according to

$$y^F_{t+h|t} = \alpha y_{t-1} + B_F F_t + \eta^F_{t+h|t} \tag{7}$$

$$y^M_{t+h|t} = \alpha y_{i-1} + B_F M_t + \eta^M_{t+h|t} \tag{8}$$

In equations (7) and (8) all variables are expressed in quarterly growth rates and h is the prediction horizon, y_t is the economic variable of interest for which we want to compute the perception and y_{t-1} is the first non overlapping lag which cleans for any persistency effect.

Recall at this point that the intent of this work is to investigate whether the

[1]See section 3.1 for details

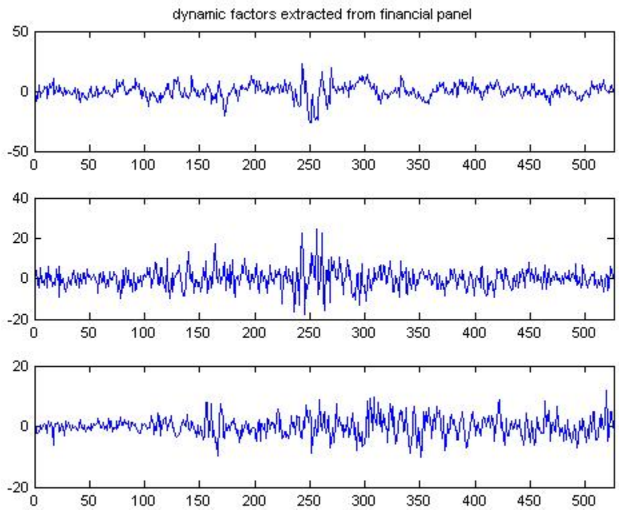

Figure 1: Dynamic component extracted from the financial panel. Whole sample 1960:1 to 2003:12

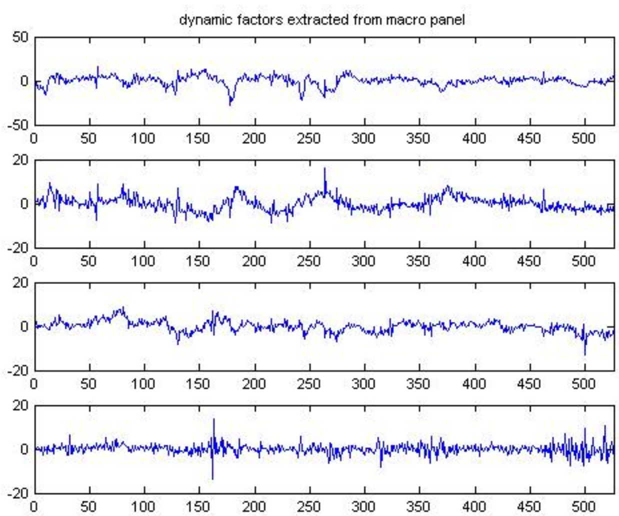

Figure 2: Dynamic component extracted from the macroeconomic panel. Whole sample 1960:1 to 2003:12

changes in the stock market returns can be explained using the difference between the two predictions. For this purpose, let $R_{t+h|t}$ be the returns on the stock market at a given horizon, and $\mathbf{y}^F_{t+h|t}$ and $\mathbf{y}^M_{t+h|t}$ two matrices collecting the defined perceptions of the selected variable - at *all* horizons - provided by the financial and the real markets respectively. The relation analyzed in this work will then be:

$$R_{t+h|t} = \gamma[\mathbf{y}^F_{t+h|t} - \mathbf{y}^M_{t+h|t}] + e_{t+h|t} \tag{9}$$

where the stock returns are also taken in quarterly growth rates.

Equation (9) describes the link - captured by the parameters in the vector γ - that connects the difference in the perceptions to the changes in the asset returns. Note that for each of the selected time horizons, the returns series will be regressed over the entire collection of differences. This will allow to discuss on one hand, the way the effect on the same return changes as we examine differences computed at several time horizons and, on the other hand, the way it changes as the horizon at which the return is considered is pushed forward.

2.3 Estimation

The estimation of the spectral density matrices of the common and the idiosyncratic components in equations (3) and (4) is performed via the discrete Fourier transform using a Bartlett lag-window of size $M = 24$, i.e. with weights $w_k = 1 - |k|/(M+1) = 1 - |k|/25$:

$$\Sigma^T_x(\omega) = \frac{1}{2\pi}\sum_{k=-M}^{M} w_k \hat{\Gamma}_k e^{-i\omega k} \tag{10}$$

where $\hat{\Sigma}_x(\omega)$ is the sample counterpart of the spectral density matrix and $\hat{\Gamma}_k$ are the sample auto-covariance matrices. The spectra are then evaluated at 101 equally spaced points in the interval $[-\pi, \pi]$, namely, at a grid of frequencies $\omega_h = \frac{2\pi h}{100}, h = 1, ..., 50$. At each frequency then the dynamic principal component decomposition is performed (see Brillinger, 1981) and the dynamic eigenvalues and corresponding eigenvectors are computed and the functions $\hat{\nu}_j(\omega)$ and $\hat{U}_j(\omega)$ are obtained. The dynamic eigenvalues are then ordered in descending order and the common shocks are recovered via the inverse Fourier transform:

$$v_{nj}^T := \frac{2\pi}{101} \sum_{h=-50}^{50} \hat{U}_n^T(\omega_h) e^{i\omega_h k} \tag{11}$$

The share of explained variance is computed according to:

$$s_j = \frac{\int_{-\pi}^{\pi} \nu_j(\omega) d\omega}{\sum_{h=1}^{n} \int_{-\pi}^{\pi} \nu_j(\omega) d\omega} \tag{12}$$

where $\nu_j(\omega)$ is the (sample) spectral density of the j-th principal component series. Equations (7) to (9) are then estimated using standard OLS.

3 Data and Econometric Framework

The panel used for this exercise is the one compiled by Stock and Watson (2005) and collects 132 macroeconomic and financial monthly series spanning the period which goes from January 1960 to December 2003.

For the factor model to be applied, all series need to be stationary processes, therefore - if necessary - the variables are transformed [2] and then normalized to have zero mean and unit variance. The database is then partitioned so that macroeconomic elements are isolated from the financial ones and the DPCs can be extracted from each of the two groups separately. It is worth notice that after a qualitative partition is performed, the two sets are filtered to obtain orthogonality, more precisely, if X_M and X_F are the original partitions, our analysis will concentrate on X_M and $\tilde{X}_F$ which is obtained as the residuals of the regression of X_F on X_M. We perform the investigation at four different time horizons, namely 1, 3, 9 and 12 months.

[2] See the Appendix for complete data list and transformations applied.

4 Empirical Results

The first set of results - summarized in tables 2 to 5 - refers to the estimates of income and inflation using the dynamic factors extracted from the macroeconomic and financial partitions.

In tables 2 and 3 we report the prediction realized for inflation and income respectively using the four macro factors denoted as f_{Mi} with $i = 1, \ldots, 4$. The first note is that not surprisingly almost all elements included in the specification play a significant role in the prediction of both inflation and income at different horizons. The relevance of all the factors included can be easily interpreted as a direct consequence of the nature of the two variables whose explanation benefits form the introduction of indices synthesizing the macroeconomic activity.

Table 2: Macroeconomic perception of inflation

	$inf_{1m,t}$	$inf_{3m,t}$	$inf_{9m,t}$	$inf_{12m,t}$
$f_{M1,t}$	0.042^{i}	-0.207	-0.541	-0.765
	(0.025)	(0.071)	(0.083)	(0.095)
$f_{M2,t}$	-0.020	0.367	0.866	1.293
	(0.050)	(0.140)	(0.166)	(0.191)
$f_{M3,t}$	0.653	-0.451	-0.300	-0.315
	(0.035)	(0.085)	(0.099)	(0.115)
$f_{M4,t}$	0.315	0.721	0.382	0.881
	(0.053)	(0.149)	(0.175)	(0.204)
$inf_{1m,t-1}$	0.687			
	(0.037)			
$inf_{3m,t-1}$		-0.421		
		(0.045)		
$inf_{9m,t-1}$			-0.186	
			(0.048)	
$inf_{12m,t-1}$				-0.174
				(0.046)

i: Coefficients and standard errors for the factors to be multiplied by $1E-04$. Standard errors in parentheses.

Table 3: Macroeconomic perception of income

	$inc_{1m,t}$	$inc_{3m,t}$	$inc_{9m,t}$	$inc_{12m,t}$
$f_{M1,t}$	0.277[i]	0.941	0.720	0.861
	(0.074)	(0.127)	(0.137)	(0.142)
$f_{M2,t}$	0.023	-0.579	-0.819	-0.562
	(0.147)	(0.258)	(0.277)	(0.287)
$f_{M3,t}$	-0.102	-0.135	-0.306	-0.224
	(0.090)	(0.160)	(0.169)	(0.174)
$f_{M4,t}$	-0.202	0.851	0.958	0.961
	(0.157)	(0.283)	(0.298)	(0.307)
$inc_{1m,t-1}$	0.042			
	(0.049)			
$inc_{3m,t-1}$		-0.457		
		(0.043)		
$inc_{9m,t-1}$			-0.344	
			(0.045)	
$inc_{12m,t-1}$				-0.346
				(0.045)

i: Coefficients and standard errors for the factors to be multiplied by $1E-04$. Standard errors in parentheses.

The picture however is not the same in the two cases in the sense that inflation seems more predictable in this setting at small horizons. Focusing on inflation prediction, there actually seems to be a pattern which distinguishes the one-month-ahead prediction from the lager horizon ones. With the exception of the second factor which is not significant, the one-month-ahead prediction of inflation quarterly growth rates responds positively to all the macroeconomic indices and its own first non overlapping lag. Moving forward in the forecast horizon the scenario changes dramatically; first, the lagged variable takes a significant and negative coefficient, second, the four factors seem to have a balancing effect with the first and the third being consistently negatively related to all forecasts while the second and the fourth maintain a positive coefficient. Moreover, the size of the effect grows as one moves towards the 12-months prediction suggesting that all the included factors behave rather as long term components.

Table 4: Financial perception of inflation

	$inf_{1m,t}$	$inf_{3m,t}$	$inf_{9m,t}$	$inf_{12m,t}$
$f_{F1,t}$	0.006^{i}	0.161	0.127	0.119
	(0.019)	(0.035)	(0.042)	(0.051)
$f_{F2,t}$	0.013	-0.013	0.052	0.019
	(0.019)	(0.034)	(0.041)	(0.049)
$f_{F3,t}$	-0.032	-0.101	0.072	-0.059
	(0.028)	(0.053)	(0.063)	(0.076)
$inf_{1m,t-1}$	0.238			
	(0.048)			
$inf_{3m,t-1}$		-0.412		
		(0.045)		
$inf_{9m,t-1}$			-0.098	
			(0.050)	
$inf_{12m,t-1}$				-0.127
				(0.049)

i: Coefficients and standard errors for the factors to be multiplied by $1E-04$. Standard errors in parentheses.

This intuition is confirmed by the coefficients reported in table 3 where the same four factors are used to predict income at the same four horizons. In this setting the short run prediction mildly reacts only to the first factor only; however a pattern similar to the one registered in the case of inflation can be found here where at larger horizons the first factor has always a positive effect on income whereas the second one brings along a negative coefficient. Interestingly also, the first two macroeconomic factors have an opposite effect on inflation and income.

A very different picture is depicted by the coefficients reported in tables 4 and 5 where inflation and income are predicted using the factors extracted from the financial set. Despite the fact that the number of significant coefficients decreases importantly, we again have the feeling that the extracted factors work better at large horizons. The reduced significance of the coefficients should not come as a surprise; income and inflation react better to macroeconomic signals than to financial ones. In particular, for both inflation and income, the second financial factor plays no relevant role for neither forecasting horizon. The third financial

Table 5: Financial perception of income

	$inc_{1m,t}$	$inc_{3m,t}$	$inc_{9m,t}$	$inc_{12m,t}$
$f_{F1,t}$	-0.052^{i}	-0.249	-0.001	-0.178
	(0.039)	(0.067)	(0.071)	(0.074)
$f_{F2,t}$	-0.042	0.078	0.036	-0.013
	(0.037)	(0.065)	(0.069)	(0.072)
$f_{F3,t}$	0.007	-0.058	-0.231	0.001
	(0.056)	(0.100)	(0.106)	(0.111)
$inc_{1m,t-1}$	0.059			
	(0.051)			
$inc_{3m,t-1}$		-0.399		
		(0.044)		
$inc_{9m,t-1}$			-0.334	
			(0.047)	
$inc_{12m,t-1}$				-0.329
				(0.047)

i: Coefficients and standard errors for the factors to be multiplied by $1E-04$. Standard errors in parentheses.

factor on the other hand seems to work only at medium horizons with a negative impact on 3-months-ahead inflation and 9-months-ahead income. Lastly, the first financial factor impacts positively inflation up to 12-months ahead prediction and negatively income somehow recreating the alternate pattern displayed by the macroeconomic factors.

The last set of results summarized in tables 6 and 7 hit the core of this investigation. Recall the purpose of this analysis is to check whether the difference in the prediction of inflation and income constructed using the macroeconomic and financial factors is a predictor for quarterly growth rates of stock market returns at different time horizons. Put differently, once we get the perception of the financial and the macroeconomic environments on inflation and income (tables 2 to 5) we use those predictions to construct difference variables which capture the excess optimism of one sector with respect to the other. In this case the difference is computed subtracting the macroeconomic perception to the financial one and therefore all the difference variables are to be interpreted as the excess optimism

Table 6: The effect of difference in inflation prediction

	$R_{t+1\|t}$	$R_{t+3\|t}$	$R_{t+9\|t}$	$R_{t+12\|t}$
$[\mathbf{y}^F_{t+1\|t} - \mathbf{y}^M_{t+1\|t}]$	3.849	2.678	-2.510	-0.525
	(1.129)	(2.212)	(2.361)	(2.312)
$[\mathbf{y}^F_{t+3\|t} - \mathbf{y}^M_{t+3\|t}]$	5.538	4.431	-7.589	-10.058
	(1.632)	(3.196)	(3.411)	(3.340)
$[\mathbf{y}^F_{t+9\|t} - \mathbf{y}^M_{t+9\|t}]$	-2.372	-2.336	0.598	1.163
	(2.046)	(4.006)	(4.277)	(4.187)
$[\mathbf{y}^F_{t+12\|t} - \mathbf{y}^M_{t+12\|t}]$	-0.277	4.098	10.548	13.614
	(1.627)	(3.186)	(3.401)	(3.329)

Standard errors in parentheses.

Table 7: The effect of difference in income prediction

	$R_{t+1\|t}$	$R_{t+3\|t}$	$R_{t+9\|t}$	$R_{t+12\|t}$
$[\mathbf{y}^F_{t+1\|t} - \mathbf{y}^M_{t+1\|t}]$	1.402	-9.124	-9.654	-12.912
	(1.808)	(3.472)	(3.837)	(3.778)
$[\mathbf{y}^F_{t+3\|t} - \mathbf{y}^M_{t+3\|t}]$	-8.134	-8.234	-3.954	-4.583
	(2.057)	(3.950)	(4.366)	(4.299)
$[\mathbf{y}^F_{t+9\|t} - \mathbf{y}^M_{t+9\|t}]$	-0.385	-7.474	-9.426	-10.810
	(1.433)	(2.752)	(3.041)	(2.994)
$[\mathbf{y}^F_{t+12\|t} - \mathbf{y}^M_{t+12\|t}]$	10.427	21.324	11.527	11.854
	(2.699)	(5.184)	(5.729)	(5.641)

Standard errors in parentheses.

of the financial sector on inflation and income at different horizons. Further we collect all the excess optimism variables and check whether the stock market actually prices such optimism. All the results suggest that it actually is the case.

In more detail, the excess optimism on the inflation prediction has a smaller overall explanatory power compared to the one associated to income. Also, while the effect of inflation is hardly identified across different horizons, the excess optimism variable for output defines a consistent pattern across all the horizons. In particular, the variables up to 9-months ahead all display large and negative explanatory power to the stock market returns. The reverse happens for the 1-year-ahead prediction. This result suggests that the market tends to resize the optimism of the financial sector when this happens in the short to medium run interpreting them as a cause of instability; on the other hand, if the effect is persistent and is captured up to the 1-year-ahead prediction then it is perceived as a positive piece of information which boosts the growth rate of stock market returns in the long term.

5 Summary and Conclusions

In this paper we argue that the stock market prices the different perception that the financial and the macroeconomic sector have on relevant variables. We run the exercise on a panel of 132 US monthly variables from 1960 to 2003 and construct excess optimism variables on inflation and income which are used as predictors for quarterly growth rates of stock market returns at different time horizons.

Our results suggest that the market responds negatively to the excess optimism on income when this happens in the short to medium run perceiving the variable as a source of instability; on the other hand, if the effect is persistent, meaning that it is captured up to the 1-year-ahead prediction, then this is interpreted as a positive piece of information which boosts the growth rate of stock market returns in the long term.

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Appendix

variable	transformation code
Personal income (AR, bil. chain 2000 $)	5
CPI-U: ALL ITEMS (82-84=100,SA)	6
Manufacturing and trade sales (mil. Chain 1996 $)	5
Sales of retail stores (mil. Chain 2000 $)	5
INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX	5
INDUSTRIAL PRODUCTION INDEX - PRODUCTS, TOTAL	5
INDUSTRIAL PRODUCTION INDEX - FINAL PRODUCTS	5
INDUSTRIAL PRODUCTION INDEX - CONSUMER GOODS	5
INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS	5
INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS	5
INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT	5
INDUSTRIAL PRODUCTION INDEX - MATERIALS	5
INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS	5
INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS	5
INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)	5
INDUSTRIAL PRODUCTION INDEX - RESIDENTIAL UTILITIES	5
INDUSTRIAL PRODUCTION INDEX - FUELS	5
NAPM PRODUCTION INDEX (PERCENT)	1
Capacity Utilization (Mfg)	2
INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS (1967=100;SA)	2
EMPLOYMENT: RATIO; HELP-WANTED ADS:NO. UNEMPLOYED CLF	2
CIVILIAN LABOR FORCE: EMPLOYED, TOTAL (THOUS.,SA)	5
CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES (THOUS.,SA)	5
UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%,SA)	2
UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)	2
UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)	5
UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)	5
UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)	5
UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)	5
UNEMPLOY.BY DURATION: PERSONS UNEMPL.27 WKS + (THOUS,SA)	5
Average weekly initial claims, unemploy. insurance (thous.)	5
EMPLOYEES ON NONFARM PAYROLLS - TOTAL PRIVATE	5
EMPLOYEES ON NONFARM PAYROLLS - GOODS-PRODUCING	5
EMPLOYEES ON NONFARM PAYROLLS - MINING	5
EMPLOYEES ON NONFARM PAYROLLS - CONSTRUCTION	5
EMPLOYEES ON NONFARM PAYROLLS - MANUFACTURING	5
EMPLOYEES ON NONFARM PAYROLLS - DURABLE GOODS	5
EMPLOYEES ON NONFARM PAYROLLS - NONDURABLE GOODS	5
EMPLOYEES ON NONFARM PAYROLLS - SERVICE-PROVIDING	5
EMPLOYEES ON NONFARM PAYROLLS - TRADE, TRANSPORTATION, AND UTILITIES	5
EMPLOYEES ON NONFARM PAYROLLS - WHOLESALE TRADE	5
EMPLOYEES ON NONFARM PAYROLLS - RETAIL TRADE	5
EMPLOYEES ON NONFARM PAYROLLS - FINANCIAL ACTIVITIES	5
EMPLOYEES ON NONFARM PAYROLLS - GOVERNMENT	5

Employee hours in nonag. establishments (AR, bil. hours)	5
AVERAGE WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFAR	1
AVERAGE WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFAR	2
Average weekly hours, mfg. (hours)	1
NAPM EMPLOYMENT INDEX (PERCENT)	1
HOUSING STARTS:NONFARM(1947-58);TOTAL FARM&NONFARM(1959-)(THOUS.,SA	4
HOUSING STARTS:NORTHEAST (THOUS.U.)S.A.	4
HOUSING STARTS:MIDWEST(THOUS.U.)S.A.	4
HOUSING STARTS:SOUTH (THOUS.U.)S.A.	4
HOUSING STARTS:WEST (THOUS.U.)S.A.	4
HOUSING AUTHORIZED: TOTAL NEW PRIV HOUSING UNITS (THOUS.,SAAR)	4
HOUSES AUTHORIZED BY BUILD. PERMITS:NORTHEAST(THOU.U.)S.A	4
HOUSES AUTHORIZED BY BUILD. PERMITS:MIDWEST(THOU.U.)S.A.	4
HOUSES AUTHORIZED BY BUILD. PERMITS:SOUTH(THOU.U.)S.A.	4
HOUSES AUTHORIZED BY BUILD. PERMITS:WEST(THOU.U.)S.A.	4
PURCHASING MANAGERS' INDEX (SA)	1
NAPM NEW ORDERS INDEX (PERCENT)	1
NAPM VENDOR DELIVERIES INDEX (PERCENT)	1
NAPM INVENTORIES INDEX (PERCENT)	1
Mfrs' new orders, consumer goods and materials (bil. chain 1982 $)	5
Mfrs' new orders, durable goods industries (bil. chain 2000 $)	5
Mfrs' new orders, nondefense capital goods (mil. chain 1982 $)	5
Mfrs' unfilled orders, durable goods indus. (bil. chain 2000 $)	5
Manufacturing and trade inventories (bil. chain 2000 $)	5
Ratio, mfg. and trade inventories to sales (based on chain 2000 $)	2
RETAIL INVENTORIES:NEW DOMESTIC PASSENGER CARS(NO.IN THOU,EOM;SA)	1
MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)	6
MONEY STOCK:M2(M1+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM TIME DEP(BIL$,	6
MONEY STOCK: M3(M2+LG TIME DEP,TERM RP'S&INST ONLY MMMFS)(BIL$,SA)	6
MONEY SUPPLY - M2 IN 1996 DOLLARS (BCI)	5
MONETARY BASE, ADJ FOR RESERVE REQUIREMENT CHANGES(MIL$,SA)	6
DEPOSITORY INST RESERVES:TOTAL,ADJ FOR RESERVE REQ CHGS(MIL$,SA)	6
DEPOSITORY INST RESERVES:NONBORROWED,ADJ RES REQ CHGS(MIL$,SA)	6
COMMERCIAL & INDUSTRIAL LOANS OUSTANDING IN 1996 DOLLARS (BCI)	6
WKLY RP LG COM'L BANKS:NET CHANGE COM'L & INDUS LOANS(BIL$,SAAR)	1
CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)	6
Ratio, consumer installment credit to personal income (pct.)	2
PRODUCER PRICE INDEX: FINISHED GOODS (82=100,SA)	6
PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS (82=100,SA)	6
PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS(82=100,SA)	6
PRODUCER PRICE INDEX:CRUDE MATERIALS (82=100,SA)	6
INDEX OF SENSITIVE MATERIALS PRICES (1990=100)(BCI-99A)	6
NAPM COMMODITY PRICES INDEX (PERCENT)	1
PCE,IMPL PR DEFL:PCE (1987=100)	6
PCE,IMPL PR DEFL:PCE; DURABLES (1987=100)	6
PCE,IMPL PR DEFL:PCE; NONDURABLES (1996=100)	6
PCE,IMPL PR DEFL:PCE; SERVICES (1987=100)	6

AVERAGE HOURLY EARNINGS OF PRODUCTION OR NON SUPERVISORY WORKERS ON PRIVATE NO	6
AVERAGE HOURLY EARNINGS OF PRODUCTION OR NON SUPERVISORY WORKERS ON PRIVATE NO	6
AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NO	6
U. OF MICH. INDEX OF CONSUMER EXPECTATIONS(BCD-83)	2
S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)	5
S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941-43=10)	5
S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)	2
S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)	5
INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)	2
Cmmercial Paper Rate (AC)	2
INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)	2
INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)	2
INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)	2
INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)	2
INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)	2
BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM)	2
BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)	2
cp90-fyff	1
fygm3-fyff	1
fygm6-fyff	1
fygt1-fyff	1
fygt5-fyff	1
fygt10-fyff	1
fyaaac-fyff	1
fybaac-fyff	1
UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.)	5
FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$)	5
FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)	5
FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)	5
FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)	5

transformations: 1 level; 2 first difference; 3 second difference; 4 log-level; 5 log-first-difference; 6 log-second-difference