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In copertina: "Un banchiere e sua moglie" (1514) di Quentin Metsys (Lovanio, 1466 - Anversa, 1530), Museo del Louvre - Parigi.

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e.mail: redazione@rivistabancaria.it - amministrazione@rivistabancaria.it
Amministrazione: presso P&B Gestioni Srl, Via G. Severano 28 - 00161 – Roma -
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MOVEMENTS AND CO-MOVEMENTS ACROSS EUROPEAN ASSET CLASSES: PORTFOLIO ALLOCATION AND POLICY IMPLICATIONS*

Michael Donadelli, Lorenzo Prosperi,
Federica Romei, Federico Silvestri**

Abstract: This paper studies the impact of changes in the dynamics of the correlation coefficients between asset returns on portfolio choices. Using weekly data from February 2002 to October 2011 on four different European asset classes, we obtain three main results. Firstly, we show that the 2007-2009 global demand collapse and the European sovereign debt crisis have largely affected the dynamics of the correlation coefficients between European asset returns. *Reductio ad absurdum*, in a post-Lehman scenario, we observe that diversification can be implemented intra-class. Secondly, in a dynamic ex-post and ex-ante mean-variance optimization (MVO) framework, we show that "stressed sovereign assets" (e.g. Greek and Italian Government Bonds) are less desirable. Thirdly, in the context of consumption-based asset pricing, we find that the resulting ex-post and ex-ante dynamic allocation reflects investors' insurance motive. We conclude by arguing that the resulting allocation might have strong implications for policymakers.

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* All original colored figures are available upon request (michael.donadelli@gmail.com)

** Michael Donadelli is a PhD student at the LUISS University, Rome, and is currently visiting the Kenan-Flagler Business School, University of North Carolina (michael.donadelli@gmail.com). Lorenzo Prosperi is a PhD student at the Toulouse School of Economics (lorenzo.prosperi@gmail.com). Federica Romei is a PhD student at the LUISS University, Rome (fromei@luiss.it). Federico Silvestri is senior financial analyst at Allianz Investment Management Spa, Milan (Federico.Silvestri@allianz.it). The views expressed here are those of the author and do not necessarily reflect those of Allianz Investment Management Spa. We thank two anonymous referees, Domenico Curcio, Giorgio Di Giorgio and Alessia Varani. All errors remain our own.

La dinamica dei coefficienti di correlazione tra diversi strumenti finanziari nel mercato europeo: implicazioni per le allocazioni di portafoglio e le politiche macroeconomiche - Sintesi Il lavoro esamina l'impatto della dinamica delle correlazioni tra i rendimenti di diversi titoli azionari ed obbligazionari sulle scelte di portafoglio. Utilizzando dati settimanali di quattro differenti asset classes europee per il periodo Febbraio 2002-Ottobre 2011, otteniamo tre risultati chiave. In primo luogo si osserva che il crollo della domanda globale nel periodo 2007-2009 e la crisi dei debiti sovrani in Europa hanno notevolmente influenzato la dinamica dei coefficienti di correlazione tra i titoli azionari ed obbligazionari europei. Per assurdo, successivamente al fallimento di Lehman Brothers, sembra esserci spazio per una diversificazione di portafoglio intra-classe. In secondo luogo, utilizzando il criterio media-varianza in un contesto dinamico, si dimostra, ex-post and ex-ante, che i titoli di paesi con gravi problemi di finanza pubblica (ad esempio i titoli di stato Italiani e Greci) sono meno appetibili. Infine, i risultati dell'ottimizzazione evidenziano una preferenza per la detenzione di assets in grado di rendere più stabili i consumi, fornendo pertanto una forma di assicurazione in caso di eventi negativi. In aggiunta, sosteniamo che le allocazioni ottenute potrebbero influire sulle decisioni dei policymakers.

Key words: dynamic correlation, mean-variance optimization, sovereign debt crisis, stressed assets

Parole chiave: correlazione dinamica, ottimizzazione media-varianza, crisi debiti sovrani, assets in sofferenza

JEL Classification: C13, G12, G15, E44

1 Introduction

The following are the main ingredients of classic portfolio theory: (i) assets' expected returns, (ii) assets' variances, (iii) correlation matrix of asset returns. It is largely accepted that the level of interaction or interdependence between markets has important consequences in terms of predictability, portfolio diversification and asset allocation. Recent empirical works indicate that, in a variety of financial markets, the first and second moments of asset returns are time-varying.[1] The goal of this paper is to study the impact of changes in the dynamics of the correlation coefficients between asset returns on portfolio choices. The study of linkages between international equity market returns is beyond the scope of this project.[2] Firstly, we examine correlation dynamics in European bond and equity markets. Secondly, we consider an investor who select his/her portfolio in a dynamic mean-variance optimization (MVO) framework. The portfolio composition is evaluated using two different approaches. In the first approach (ex-post MVO), our investor estimates the first and second moments of asset returns in an ex-post dynamic framework. This method is flexible, but it relies strongly on assumptions about the way in which investors process news. In the second approach (ex-ante MVO), the investor evaluates means and variances by employing a specific model (i.e. VAR, DCC-GARCH). In this model only the most recent information affects the dynamics of the optimization inputs. While the ex-post analysis is able to capture the impact of the dynamics of the correlation coefficients on optimal weights, the ex-ante analysis might represent a tool to study the impact of portfolio allocations' changes on policymakers' decisions. The last two issues are the foundation of this paper.

Using weekly data from February 2002 to October 2011 on eleven European assets, belonging to four different classes, we find that the correlation coefficients between European asset returns have a strong time-varying component and that the ex-post and the ex-ante portfolio compositions are very volatile. We show that optimal weights dramatically change in the post-Lehman world.[3] In particular, the MVO optimizer underinvests in Greek and Italian debt. We observe that Greek and Italian

1 See Bekaert and Harvey (1995, 2000), Donadelli and Prosperi (2012a), Erb et al. (1994), Kaplanis (1988), among many others.

2 For a detailed discussion on stock market linkages see Cheung and Mak (1992), Choudhry (1997), Chowdhury (1994), Dunis and Shannon (2004), Kasa (1992) and Ng (2002), among others.

3 Throughout the paper we use the terms post-Lehman and post-crisis interchangeably.

bonds are as risky as stocks, and do not provide any insurance benefits. Furthermore, we find that they perform worse than stocks. The result is confirmed by the Sharpe ratios reported in Table A.3. It turns out that these assets are less desirable.

We obtain four main results. First, we find that the correlation coefficients between different European Government bond returns are either very low or negative in the post-Lehman world. We rely on the German, Greek and Italian debt. We argue that such result allows for intra-class diversification benefits. Second, we show that the resulting ex-post MVO portfolio allocation is heavily affected by the unusual dynamics of the correlation coefficients between European asset returns. Third, in a MGARCH setup, we firmly support the sensitivity of portfolio allocations to time-varying correlations. Last, in a consumption-based asset pricing framework, we observe that our allocations embody insurance benefits motive.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes data. Section 4 studies the dynamics of the co-movement between European asset returns. We focus on European stressed assets. Section 5 implements the ex-post and ex-ante dynamic MVO. Section 6 concludes.

2 Literature review

Our paper adds to a vast literature that studies the effects of the time-varying co-movement between asset returns on optimal portfolio choices. The approach in this paper is unique in that we focus on the dynamic allocation of a MVO investor in an "ad hoc" investment scenario. We rely on eleven European assets belonging to four different classes in the post-Lehman world.

The goal of modern portfolio theory is to optimally allocate wealth among different asset classes while considering the trade-off between risk and return. The single period portfolio optimization, firstly formulated by Markowitz (1952), uses mean and variance to maximize the expected return of the portfolio given a certain level of risk, or to minimize the risk of a portfolio given the expected return. It turns out that a mean-variance optimal portfolio allocation is very sensitive to changes in the inputs. In a dynamic context, an optimal allocation considers that expected returns and cross-asset correlations vary through time. Ball and Torous (2000) argue that the time-varying nature of the variance-covariance matrix is key in solving portfolio choice models. They study, empirically, the co-movement of a number of international stock market indexes, and find that the estimated correlation structure is changing over time. They observe that such variation depends on economic policies, the level of capital market integration, and relative business cycle conditions. They argue that ignoring the time-varying component of the correlation might generate naive portfolio choices.

Many other empirical asset pricing studies find that correlation coefficients change through time. Kaplanis (1988), fitting time-series models to rolling correlation measures of equities in 15 national markets, shows that correlation is not constant. Erb et al. (1994) argue that the change in correlations through time is linked to economic activity. They show that equity correlations are higher than usual if two countries are simultaneously in economic recession. Ledoit et al. (2003) show that the level of correlation depends on the phase of the business cycle. Bekaert and Harvey (1995, 2000) provide direct evidence that market integration and financial liberalization change the correlation between the global stock market index return and the emerging markets' stock returns.[4] Moskowitz (2003) documents that covariances across portfolio returns are highly correlated with NBER recessions and that average correlations are highly time-varying. Ang and Chen (2002) show that the correlation between US stocks and the aggregate US market is much higher during extreme downside movements than during upside movements. Simi (2010) extends the well known Black and Litterman (1990) model including time-varying volatility. He obtains "superior" portfolio returns. Chong and Miffre (2012) find that the conditional return correlations between S&P500 index and commodity futures fell over time.

In recent years, financial literature focuses on time-varying volatility estimations. Longin and Solnik (1995), using a GARCH estimation model and imposing the null hypothesis that the correlation between equity markets is constant, conclude that correlation is not constant. To allow for time-varying cross-assets correlation, Engle (2002) introduces a multivariate GARCH, namely DCC-GARCH. Billio et al. (2006) extend the DCC-GARCH model proposed by Engle (2002) by abstracting from the assumption of common correlation dynamic by block-estimation. Cappiello et al. (2006) extend Engle's (2002) model. They include series-specific news impact, smoothing parameters and

4 Using monthly data for 19 emerging and 13 developed stock markets across six regions over the period January 1988-December 2011, Donadelli and Prosperi (2012b) obtain a similar result.

conditional asymmetries in correlation dynamics. Han (2006) proposes a dynamic factor multivariate stochastic volatility (DFMSV) model that allows the first two moments of returns to vary over time for a large number of assets.[5] Gupta and Mollik (2008) use a computationally efficient DCC-GARCH model for estimating time-varying correlations, and find that the correlations between Australia's equity return and emerging markets' equity returns change over time.

3 Data

3.1 Data description

We employ a limited number of "ad hoc" European assets. Details on downloaded data are provided in Table A.1. All time series are weekly total return indices (i.e. reinvested dividends are included) and run from 12/02/2002 to 04/10/2011. Asset weekly returns are easily computed from the total return indices.[6] Our indices belong to four different European asset classes (i.e. Government Bonds, Corporate Bonds, Cash and Equity). To consider short-term and long-term assets in the analysis, we download both 2Y and 10Y maturity government bond indices. The choice to consider the debt of only three European governments reflects the main goal of the paper. The German, Greek and Italian government bond markets have been largely discussed in the last three years.[7] In our exercise we also employ a short-term (i.e. 1-3 years) corporate bond index and a long-term (i.e. 7-10 years) corporate bond index. We rely on the BOFA ML Emu Corp Index with rating equal to A (i.e. upper medium grade). A liquid asset is represented by the JPM Euro Cash

5 Note that the Han's (2006) model is more parsimonious than the MGARCH model.

6 Returns are defined as $R_{i,t} = \frac{TRI_{i,t}}{TRI_{i,t-1}} - 1$ where $TRI_{i,t}$ denotes the total return index of asset i at time t.

7 We report here some relevant facts. Germany is still rated AAA. In contrast, Italy and Greece have been downgraded during the last years. Here below a brief chronology of the most relevant events. Fitch Ratings cuts Greece's sovereign credit rating to BBB+ from A-, Standard & Poor's cuts Greece's sovereign credit rating to BBB+ from A-, Moody's cuts Greece's sovereign credit rating to A2 from A1 (as of December 2009); Standard & Poor's downgrades Greece's sovereign credit rating below investment-grade status (as of April 2010); Moody's cuts the sovereign debt rating of Greece to Ba1, junk status (as of June 2010); Fitch Ratings downgrades Greek sovereign debt to BB+, or junk status (as of January 2011); Standard & Poor's downgrades Italy's sovereign debt rating from A+ to A- (as of September 2011); Fitch Ratings cuts the sovereign debt rating of Italy from AA- to A+ (as of October 2011).

Index (3 months). We argue that it can be easily used as a risk-free rate proxy.[8] To conclude, we use two different sector-based equity indices, a defensive sector (i.e. MSCI Emu Utilities), showing an average beta lower than one, and a cyclical sector (i.e. MSCI Emu Industrial) with an average beta greater than one.

3.2 Summary statistics

Summary statistics of European asset returns are reported in Tables A.2 and A.3 for the *full sample* (i.e. February 2002-October 2011) and *post-Lehman world* (i.e. November 2008-October 2011), respectively. For the full sample, we observe four main ex-post statistical features of asset returns: (i) the Euro cash index carries the highest return per unit of risk; (ii) short- and long-term Greek bonds display negative excess returns (i.e. negative Sharpe ratios); (iii) the standard deviations of short- and long-term German and Italian bonds are surprisingly similar; (iv) equities, corporate bonds, Greek bonds and short-term Italian bonds show negative skewness.[9] In the post-Lehman world, results (i)-(iv) are partially confirmed. Firstly, we find that the Sharpe ratio of the cash index is negative. Secondly, we observe that corporate and "safer" sovereign bonds carry the highest Sharpe ratios. Greek government bond returns still display negative Sharpe ratios (i.e. negative average excess returns). The short- and long-term Italian government bond market still provides positive average excess returns but are highly volatile (i.e. lower Sharpe ratios). We find that the recent 2007-2008 subprime crisis has weakened some European assets. Fig. A.1 displays the weekly compounded performance of our eleven European assets' returns. Performances in Fig. A.1 are based on an hypothetical investment of $100 on 12/02/2002. As expected, equity returns are much more volatile than bond returns. Industrials and utilities returns follow a similar pattern. The recent collapse of the Greek bond market is evident (see red and pink lines in Fig. A.1). The increasing performance of the 10Y German bonds reflects the "European sovereign debt crisis" (i.e. see turquoise line in Fig. A.1). The German debt is perceived as safe investment (i.e. flight-to-quality effect). We observe that stressed countries have offered a low risk-adjusted

8 The return of a riskless security should present a lower standard deviation than the stock's returns (see Table A.2 and A.3).

9 Note that our results are clearly influenced by the 2007-2009 sub-prime crisis as well as by the current European sovereign debt crisis.

performance in the post crisis sample. This seems to represent the main reason forcing investors to short sell such assets.

4 Dynamics in the correlation of European asset classes: evidence from the pre- and post-crisis world

Correlations between asset returns are key in portfolio allocation. Several studies support the idea that the correlation coefficient is not constant over time. Correlation coefficients' changes affect portfolio choices as well as the portfolio performances. Firstly, by exploiting the behavior of the German and Italian long-term government bond markets, we review the concept of correlation. Secondly, we study correlation coefficients between European asset returns in a purely dynamic context.

4.1 Evidence from the German and Italian bond markets

The fact that two phenomena display certain behavioral similarities in time, space, or in combination of these, does not necessarily imply that they are cause and effect. David Hume, a Scottish philosopher, claims that one believes event A causes event B simply because she/he is in the habit of expecting event A to be followed by event B. He provides the following example: if one hears a rooster's crow every morning, for many mornings, and sequentially sees the sun rising, and if one only sees the sunrise after the rooster's crow, then one automatically concludes that rooster's crow "causes" the sun to rise. The two events, however, are merely correlated (i.e. the rooster's crow does not cause the sun to rise). The concept of correlation is clearly illustrated in Fig. B.1 which plots the 10Y Italian Bond (IT 10Y) and 10Y German Bond (BD 10Y) total return indices (left panel) and redemption yields (right panel). The correlation seems to be highly positive for the period 2002-2010. If the last two years are considered, it becomes negative. The correlation coefficients for the period 2002-2008, 2009-2010 and 2010-2011 are equal to 0.99, 0.89, and -0.70, respectively. Over the full sample, the correlation is 0.95. We expect that such empirical evidence heavily influences the MVO allocation. A naïve investor faces the risk to hold an optimal allocation in which she/he implicitly assumes that the IT 10Y and the BD 10Y move in the same direction. In contrast, a wise investor should recognize that a change in the dynamics of the correlation between two assets might dramatically affect the performance of the portfolio. The area between the red and blue lines in Fig. 3.1 represents the spread between the Italian and German bonds. The spread indicates the different risk levels of the two debtors, and it is generally influenced by the following factors: i) the performance of the economy; ii) the public debt; iii) the stability of the government; iv) flight to quality. In general, the spread between two different European government bonds is relatively small. Specifically, the spread began to widen in September 2008, when Lehman Brothers declared bankruptcy and German yields decreased (i.e. flight-to-quality effect). We observe a significant jump in April 2010, when Greece officially asked for financial support. The third and strongest increase is documented in July 2011, when investors started to sell large amounts of Italian bonds. The Italian-German yield spread widened and the returns of these two assets began to move in opposite directions.

4.2 European asset returns' co-movements: some stylized facts

Correlation coefficients as well as expected returns vary through time. Such time-varying nature is captured in Fig. B.2 which reports the estimated correlation matrix for six different windows. The variation in the composition of colors across matrices provides the intuition. The changes in the concentration of *dark red* over different windows for each pairwise correlation are evident.

It is largely accepted that this time-varying component might heavily affect the optimization process of an investor. If government-based asset classes are held by international investors, then the dynamic allocation might also affect policymakers' decisions. In a pure dynamic framework, we estimate correlation coefficients using a rolling window of 60 weeks (i.e. 15 months).[10] Estimation results are presented in Figs. B.3-B.5. We report the rolling window estimates of the correlation coefficient between each asset *i* and all other assets. We confirm the presence of a strong time-varying component.[11] The impact of the crisis on the dynamics of the correlation coefficients is evident, especially when the last 100 windows are analyzed. We stress that in some cases the sign of the co-movement between two different asset returns changes direction. For example, Fig. B.3 shows that the correlations between the IT2Y and GR2Y bonds and the industrial equity returns become positive in the post-Lehman world. Over the last 60 windows, the average correlations are 0.03 and 0.16, for

10 The number of observations for estimation is 60. The first estimation window is 12/02/2002-01/04/2003. The second is 19/02/2002-08/04/2003. There are 444 estimation windows. The final estimation window is 17/08/2010-04/10/2011.

11 See also Bollerslev et al. (1988), and Bekaert and Harvey (1995), Donadelli and Lucchetta (2013), among many others.

the IT2Y and the GR2Y, respectively. The correlations between the IT2Y and GR2Y bond and the utilities equity returns are also positive over the last 60 windows, 0.34 and 0.20, respectively. In normal times or tranquil periods, correlations between stock and bond returns are negative (i.e. when stocks perform badly investors prefer to hold bonds). The result suggests that such stressed bonds are considered as risky as stocks. We also find that the correlation coefficients between the German and the Italian and Greek Government bond returns follow a decreasing path, surpassing the zero bound around window 350. Over the last 60 windows, the average correlation between the IT10Y and GR10Y and the BD10Y bond returns is negative, -0.01 and -0.12, respectively. The average correlation between the IT2Y and GR2Y and the BD2Y is also negative, -0.12 and -0.10, respectively. The change in the sign of the correlation coefficient between asset returns belonging to the same asset class gives rise to intra-class diversification benefits. The result is clear in Table 5.1 which reports the mean and the variance of weekly rebalanced weights for the pre- and post-crisis period. In the post-crisis period, average weights on the short and long term German bond market are positive, 10.57% and 8.90%, respectively. In contrast, average weights on the Greek and Italian bond markets are either negative or close to zero. In absence of intra-class diversification benefits (i.e. positive correlation between the Greek and Italian bond returns and German bond return in the post-crisis sample), average optimal weights on the short- and long-term German bond market would be also close to zero. To sum up, in the post-crisis sample, stressed assets show a negative correlation with "safe" investments and positive correlation with stocks. Since stocks are usually correlated with the business cycle, we argue that such bonds are risky because they do not provide an insurance against bad states of nature.

5 Asset co-movements, MVO and sovereign debt crisis

5.1 Ex-post MVO

We develop a simple investment game to study the effects of the unusual dynamics of the correlation coefficients between our eleven European asset returns on portfolio allocation. In particular, the goal of this exercise is to show that an MVO investor tends to have preferences for "non-stressed assets". We rely on the time-varying nature of the cross-asset correlations. A time-varying correlation matrix forces investors to dynamically optimize their portfolios. Modern practices utilizing dynamic optimization techniques are much more common than in the past. However, a small fraction of investors still use static or low-frequency rebalanced portfolios.[12] The nature of our investment game requires the following assumptions:

Assumption 1: a portfolio can be rebalanced (on weekly basis) at zero cost

Assumption 2: short positions are permitted

Assumption 3: long-term information is processed "under the veil of ignorance"

While *assumption 2* might be innocuous, *assumption 1* may appear too strong. We justify this assumption as follows: (i) all the assets selected for this exercise are very liquid and largely traded; (ii) a constant portfolio rebalancing cost function across asset classes do not affect the ultimate goal of our exercise. In this ex-post MVO setup, we also assume that "under the veil of ignorance", the investor weighs equally all past information.[13] In practice, the investor processes very old information in order to form expectations on the return and variance-covariance matrix for the next period. In this setting, the investor is not able to take a stand on the way in which past data may affect future prices. The information processing assumption determines a low frequency adjustment. It turns out that each new information has a small impact on the estimated moments, thus the final allocation changes slowly over time (i.e. smoothed allocation). Dynamic optimal weights are first obtained by employing a standard ex-post optimization technique. The optimization problem aims to minimize the overall variance of the portfolio subject to a pre-determined expected return and a wealth constraint. Formally, the problem is

$$\begin{aligned} &\min_{\{w\}} \quad w'\Sigma w \\ &\mu_p = w'r \\ &1 = w'1 \end{aligned} \tag{5.1}$$

where $\boldsymbol{w}$, $\boldsymbol{r}$ and $\mathbf{1}$ are (N 1) vectors representing weights, returns and

12 We justify the use of this "naive strategy" as follows: (i) algorithm implementation is much more easier, especially for "naive" investors; (ii) high-frequency portfolio rebalancing is costly and sometimes subject to liquidity problems.

13 Note that we estimate the first and second moment of asset returns by simply computing the sample average and the sample variance over the past 60 weeks.

ones, respectively, μ_p represents the portfolio expected return, and N is the number of assets. The variance-covariance matrix Σ represents the risky component. Using historical returns and historical variance-covariance matrix, problem (5.1) is replicated on weekly basis. In practice, optimal weights are computed, according to Eq. (5.1), using a rolling window of 60 weeks (i.e. optimization problem's inputs are not constant). Figs. C.1 and C.2 show the ex-post dynamic allocation in the pre- and post-crisis period, respectively. The pre-crisis period spans from February 2002 to November 2008 (i.e. 295 windows), and the post-crisis period from December 2008 to October 2011 (i.e. 89 windows). As expected, the dynamic portfolio compositions show key differences in the two sub-samples. We obtain the following results: (i) large long positions in cash (i.e. risk-free asset) in both sub-samples; (ii) small short positions in long-term German, Greek and Italian debt over the last 50 windows of the pre-crisis period; (iii) constant long positions on German bonds, and constant small short positions in short-term and long-term Greek, and Italian debt, in the post-crisis period; (iv) constant short positions in short-term and long-term corporate debt in the post-crisis period; (v) average positions, either negative or positive, on stocks (i.e. industrials and utilities), Greek, Italian and corporate debt are very small; (vi) the allocation in the post-crisis period is more stable over time. Results are summarized in Table 5.1 which reports the mean and variance values of the ex-post weekly optimal weights for the pre- and post-crisis sample. Columns two and three show that the average long positions in CASH are equal to 84.80% and 95.57% in the pre- and post-crisis period, respectively. Not surprisingly, the optimizer largely prefers the asset with the lowest variance. Optimal weights reflect one of the common issues, or criticisms, of traditional mean-variance optimization (i.e. corner solution). On the one hand, the MVO does not provide a well diversified portfolio, and on the other, we observe that the change in the sign of the correlation between European government bond asset returns (i.e. German, Greek and Italian government bonds) allows for intra-class diversification benefits. The dynamics of the optimal weights suggest that the MVO investor finds stressed assets less desirable. After the crisis, both the Italian and Greek bonds show a low risk-adjusted performance. The demand of these assets collapses, that is, investors are unwilling to hold assets which do not provide gains in bad states of nature (i.e. economic and financial crises).

Asset	Mean		Variance	
Period	Pre-Crises	Post-Crises	Pre-Crises	Post-Crises
IT02Y	1.88	-0.81	4.20	0.13
IT10Y	-2.24	-2.67	0.17	0.07
BD02Y	8.80	10.57	2.59	0.11
BD10Y	-0.81	8.90	0.27	0.13
GR02Y	5.29	-0.94	1.17	0.04
GR10Y	-2.70	0.91	0.13	0.01
CORP 1-3Y	4.54	-9.46	4.41	1.53
CORP 7-10Y	2.72	-4.47	1.32	0.09
CASH	84.80	95.57	14.28	1.42
UTIL	-3.31	2.87	0.19	0.08
IND	1.03	-0.46	0.12	0.07
TOT	100.00	100.00		

Table 5.1: This table reports the mean and the variance of weekly rebalanced weights - computed as in Eq. (5.1) and illustrated in Figs. C.1 and C.2 - over the pre- and post-crisis periods. Statistics are computed employing 295 and 89 different weekly allocations for the pre- and post-crisis period, respectively. Values are expressed in percentage points. Average weights add up to one.

5.2 Ex-ante MVO

The ex-post dynamic MVO presented in section 5.1 suggests that international investors tend to take short positions on Italian and Greek sovereign debt. The result is largely influenced by the sign of the correlation coefficients between assets. The goal here is to confirm such results adopting an alternative technique. The choice to replicate our investment game using an ex-ante approach is motivated by the need for robustness. In contrast to the ex-post exercise, the ex-ante resulting allocation does not strongly depend on the way in which the investor processes information. Furthermore, this exercise might be beneficial for policymakers who are involved in the bond auctions process. Our previous results are heavily influenced by the way in which the dynamic variance-covariance matrix is estimated. In this section, via an ex-ante short-term estimation of the expected returns and the variance-covariance matrix, we show that similar dynamic allocations can be obtained. This empirical analysis relies on the short term view of an investor who desires to allocate financial resources in a MVO context (i.e. according to Eq. (5.1)). In practice, we estimate a VAR-MGARCH to forecast the first (i.e. expected return) and the second moment (i.e. correlation matrix) of asset returns. These forecast values represent the new input of problem (5.1). We stress that assumptions (1)-(2) are still at work. We emphasize that the processing information activity is different. In this setup, the investor only use recent data on asset returns to predict the first and second moments, and in order to do so, she/he will optimally weigh past information according to a standard time series model. This results in a high frequency trading strategy where the final allocation changes dramatically period-by-period.

5.2.1 The procedure

It is assumed that investors forecast the dynamics of asset returns according to a VAR(2) and a MGARCH(1,1). In particular, a representative investor assumes the following

$$r_t = \mu + A_1 r_{t-1} + A_2 r_{t-2} + \varepsilon_t \qquad \varepsilon_t \sim N(0, H_t) \tag{5.2}$$

where r_t is the vector of asset returns. The AIC and BIC criteria select two lags in the VAR. We argue that the number of optimally selected lags is sufficient to clean residuals from serial correlation. Under this specification the expectation of asset returns is given by a linear combination of past returns. Formally,

$$E[r_{t+1} \mid I_t] = \mu + A_1 r_t + A_2 r_{t-1}$$

where I_t is the information set available at time t. The way in which investors absorb past information and use them to make forecasts might be questioned. In particular, we exclude the hypothesis that older information may influence short term dynamics. In addition, we assume that all price-sensitive news are embodied in t and t–1. Due to the curse of dimensionality issue and the relatively small sample size, we need to reduce the number of parameters to estimate. Consequently, we do not include older information. Nevertheless, we show that the choice of lags is accurate enough to clean the residuals. Moreover, we assume that the expectation on the second moment of r_{t+1} is determined by a MGARCH model. The latter implies that a shock on the variance at time t for one asset has a positive effect on the future variance of that asset, as well as on the variance of the other assets composing the investor's portfolio. A central issue in the MGARCH literature relies on the specification of the assets' correlation dynamics. To mitigate the problem of the increasing number of parameters to estimate, we adopt the DCC-GARCH model of Engle (2002). We model the variance-covariance matrix H_t as follows

$$\begin{aligned} H_t &= D_t P_t D_t \\ D_t &= diag\left(h_{1t}^{\frac{1}{2}}, \ldots, h_{1N}^{\frac{1}{2}} \right) \\ P_t &= (I \otimes Q_t)^{-\frac{1}{2}} Q_t (I \otimes Q_t)^{-\frac{1}{2}} \\ Q_t &= (1-a-b)S + a\varepsilon_{t-1}\varepsilon_{t-1}^{'} + bQ_{t-1} \end{aligned} \tag{5.3}$$

where S_t is the unconditional correlation matrix and $a + b < 1$. In this model the matrix Q_t plays a crucial role. It is standard for practitioners and econometricians to model the conditional variance of each asset via GARCH(1,1), represented by D_t.[14] The conditional correlation is specified by P_t and Q_t. The latter is specified by a VARMA. We stress that our specification is very parsimonious. Laurent et al. (2010) show that alternative MGARCH specifications do not provide significantly better forecasts than the DCC model of Engle (2002).

To estimate the parameters, we proceed as follows. First, we estimate a VAR as specified in Eq. (5.2). Second, we employ the VAR's residuals to implement the DCC-MGARCH. As stated, the VAR(2) specification is used to forecast returns, and the number of optimally selected lags is required to clean the series from serial correlation. The latter argument is key for the DCC-GARCH estimation. In Table 5.2 we report the Ljung-Box and Jarque-Bera tests for the VAR's residuals. The second column shows that the serial correlation of the first moment of the residuals is eliminated in most cases. The third column shows the presence of ARCH effects (i.e. the null hypothesis of no serial correlation in the squared of the residuals is rejected). As usual with financial data, the normality hypothesis is rejected (see 4th column of Table 5.2). The last column of Table 5.2 reports the adjusted r-squared of the VAR estimations. We find that the VAR does a very poor job for the two stock indices, and for the Italian and German bonds. Instead, it does a good job for the CASH index, the Greek bonds and the corporate bonds. We argue that the VAR's estimates do not provide a clear pattern to predict portfolio's returns. In keeping with the purpose of this paper, we decide to skip the discussion on all estimated coefficients. We believe that a discussion on 253 coefficients might be tedious for the reader. Since the model is too parameterized, the

14 Note that the univariate GARCH models can have different orders. Often the simplest model, GARCH(1,1), is adequate.

choice of a VAR(2) might affect the power of the t-test. We stress that 253 coefficients have to be estimated using only 501 observations, implying weak inference. Hence, the adjusted r-squared represents a decent measure to capture the performance of the model employed to forecast asset returns.

Asset	Q-stat res	Q-stat res2	JB-test	$\bar{R}$
IT2Y	51.858	265.633	1499.249	0.109
	(0.000)	(0.000)	(0.000)	
IT10Y	26.048	89.042	61.571	0.078
	(0.164)	(0.000)	(0.000)	
BD2Y	22.536	100.307	51.985	0.073
	(0.312)	(0.000)	(0.000)	
BD10Y	23.698	199.650	2231.966	0.033
	(0.256)	(0.000)	(0.000)	
GR02Y	22.363	159.546	1050.756	0.385
	(0.321)	(0.000)	(0.000)	
GR10Y	16.136	153.461	226.793	0.248
	(0.708)	(0.000)	(0.000)	
CORP 1-3Y	18.166	141.128	34.305	0.281
	(0.577)	(0.000)	(0.000)	
CORP7-10Y	59.399	82.408	40972.024	0.302
	(0.000)	(0.000)	(0.000)	
CASH	58.870	85.217	9750.934	0.863
	(0.000)	(0.000)	(0.000)	
UTIL	16.447	48.444	742.227	0.051
	(0.689)	(0.000)	(0.000)	
INDUSTR	13.815	93.657	327.133	0.086
	(0.840)	(0.000)	(0.000)	
				N. Obs. 501
				N. Var. 23

Table 5.2: Tests on VAR's residuals. The first and the second columns report the Ljung-Box Q-test on the residuals and on the squared residuals, respectively. The third column reports the Jarque-Bera normality test. P-values are reported in parenthesis. The $\bar{R}$ of the estimated VAR(2) are presented in the last column.

We estimate the MGARCH, via the Engle's (2002) procedure, using the VAR's residuals. A standard approach to evaluate the performance of a GARCH model is to compare the squared residuals of the VAR process to the diagonal variance covariance matrix . These two series are plotted in Fig. D.2. For completeness, the mean absolute error values (MAE) are also presented (see Table 5.3).[15] For the equity indices, as well as for

15 We recall that the mean absolute value for the GARCH estimation of the asset j is defined as follows

$$MAE_j = \frac{1}{T}\sum_{t=1}^{T} |\varepsilon^2_{j,t} - h_{j,t}|$$

where $\varepsilon^2_{j,t}$ is the squared of VAR residuals for equation j and $h_{j,t}$ is the (i, j) element of the matrix H_t.

the Greek bonds, the DCC-GARCH does not perform well. We find that the periods of high volatility are more persistent than in the data. If the last 200 windows and the Greek bond market are considered, our empirical regularity, is exacerbated. It turns out that that the result is mainly driven by the European sovereign-debt crisis and consistent with the MAE reported in Table 5.3. In fact, the highest MAE values are obtained for the equity indexes and Greek bonds returns. Instead, the model does a good job for the risk-free asset (i.e. CASH).
In this investment game, we assume that the investors update their beliefs according to the following estimates: (i) the VAR is used to predict the conditional mean; (ii) the MGARCH is implemented to get the one-period ahead conditional variance. Thus, the usual MVO applies. As in section 5.1, the investor is allowed to rebalance the portfolio freely (on weekly basis). Fig. E.1 reports the dynamic composition of the portfolio accounting for the “new” MVO inputs. As expected, given that investors update their beliefs using only the last two past observations, the portfolio composition is very volatile. Via standard filtering techniques, it is possible to extrapolate the time-varying trend of our asset-by-asset dynamic allocation (see red solid line in Fig. E.1).

BD2Y	0.00017	CASH	0.00000
BD10Y	0.00327	CORP 1-3Y	0.00020
IT2Y	0.00032	CORP 7-10Y	0.00199
IT10Y	0.00316	UTIL	0.04821
GR02Y	0.01413	INDUSTR	0.07222
GR10Y	0.01715		

Table 5.3: DCC-MGARCH: Mean Absolute Error (annual)

This analysis confirms most of the results obtained via ex-post MVO. We confirm the presence of a constant long (large) position in CASH both in the pre- and post-crisis sample. We also confirm the presence of short positions in the Italian and Greek debt market. In contrast, we are not able to confirm the general preference for German bonds in both maturities. We obtain long (small) position in the long-term German bond market only. Long (large) positions are taken on the CORP 1-3Y bond. As in the ex-post MVO, our ex-ante findings display corner solutions. In particular, resources are primarily allocated in three assets (i.e. CASH, CORP 1-3Y and BD10Y).

5.2.2 Some final remarks

This ex-ante dynamic analysis has been conducted for robustness purposes (i.e. to check ex-post MVO results). The analysis can be very useful to evaluate the short term dynamic behavior of financial markets. We argue that the patterns chosen by the MVO investor to insure their resources might have strong policy implications. In particular, we rely on the challenge faced by the Greek and Italian governments in selling their debt through the auction process. The dynamic allocations presented throughout this paper could represent a signal for the policymakers who desire to allocate the debt at the lowest possible cost.[16]

The dynamics of the ex-ante allocations presented in Fig. E.1 suggests that some asset classes are perceived to be very risky. We refer to the short-term and long-term Greek and Italian government bonds. From a computational point of view, our allocations are driven by the dynamics of the correlation matrix. The behavior of the correlation coefficients across European asset classes is well documented in Figs. B.3-B.5. In a MGARCH framework, using the short-term Italian bond as benchmark, we confirm such behavior (see Fig. D.1).[17] We argue that stressed asset returns are positively correlated with the business cycle. The reason for this positive correlation is that with high level of debt an economic recession would reduce fiscal resources increasing the risk of default of the country. The occurrence of an economic recession would not induce the default of countries with a low and stable public debt and they will continue to payoff even in bad states.

We conclude by arguing that the resulting allocation has also a strong consumption-based foundation. The joint analysis of Figs. A.1, C.1, C.2, E.1 provides evidence for the existence of the "insurance motive". In a consumption-based model, the desirability of an asset reflects its ability to smooth consumption. Hence, agents desire assets that pay off in bad states of nature (i.e. when consumption is low, thus the marginal utility of consumption is high). To satisfy this need (i.e. to be insured against bad times), they pay a premium. In periods characterized by expected exploding stock market volatility and high economic uncertainty, the

16 The cycle we have in mind is as follows. Higher yields on secondary bond markets (i.e. low demand), imply a higher interest paid by governments on the primary market when they need to issue bonds to finance their debt. A higher interest rate level implies that governments might be unable to reduce taxes or increase public expenditure in order to stimulate economic growth. The impossibility to stimulate growth worsens public debt, thus governments pay higher interest rates on the outstanding amount of debt. The vicious cycle is evident.

17 The full set of dynamic cross-asset conditional correlations is available upon request.

insurance motive phenomenon is exacerbated. Fearing the default of a couple of Mediterranean countries' and discounting the high uncertainty of international stock markets, agents tend to allocate wealth in safe securities (i.e. in securities that payoff in bad states). In our exercise, we find the following "consumption-based" results: (i) a large fraction of wealth in constantly invested in the risk-free market (i.e. CASH); (ii) an increase in the demand of "safe Government bond" in the post-crisis period; (iii) a sharp decrease in the demand of risky assets. To be insured against bad times, international investors' find safe assets more desirable. It turns out, that the portfolio is fully described by long positions in CASH and German bonds (see Figs. C.1 and C.2). The higher demand of German debt, reflect the higher price of German bonds as well as the higher spread between the 10Y Italian and German yield (see Fig. B.1).

6 Conclusion

The time-varying nature of the correlation matrix of asset returns is key in dynamic MVO. In a dynamic ex-ante and ex-post MVO context, optimal weights are heavily affected by changes in the correlations between asset returns. We show that the change in the sign of the correlation coefficients between European government bond asset returns allows for intra-class diversification benefits. We find that the amount of wealth optimally invested in the Italian and Greek bonds has followed a declining path (i.e. investors find stressed assets less desirable). The average amount of wealth optimally invested in the short- and long-term Greek and Italian government bond markets is close to zero (or negative). In contrast, we observe a constant long position in the short- and long-term German government bond market. Finally, we show that a large fraction of the investor's wealth is constantly allocated in CASH, both in the pre- and post-crisis period. Results suggest that the ex-post and ex-ante dynamic allocations are mainly driven by the sign of the correlation coefficients between European government bond asset returns, and strengthened by investor's insurance motive.

References

Ang, A. and Chen, J. (2002). Asymmetric Correlations of Equity Portfolios. *Journal of Financial Economics*, 63, 443-494.

Ball, C. A. and Torous, W. N. (2000). Stochastic Correlation Across International Stock Markets. *Journal of Empirical Finance*, 7, 373-388.

Bekaert G. and Harvey C. R. (1995). Time-Varying World Market Integration. *Journal of Finance*, 50, 403-444.

Bekaert G. and Harvey C. R. (2000). Foreign Speculators and Emerging Equity Markets. *Journal of Finance*, 55, 565-613.

Billio, M. Caporin, M. Gobbo, M. (2006). Flexible Dynamic Conditional Correlation multivariate GARCH models for asset allocation. *Applied Financial Economics Letters*, 2 (2), 123-130.

Black, F. Litterman, R. (1990). Asset Allocation: Combining Investors View with Market Equilibrium. Fixed Income Research Goldman Sachs & Company.

Black, F., Derman, E. and Toy W. (1990). A one-factor model of interest rates and its application to treasury bond options. *Financial Analysts Journal*, 46(1), 33-39.

Bollerslev, R.F. and Wooldrige, J.M. (1988). A Capital Asset Pricing Model with Time-Varying Covariances. *Journal of Political Economy*, 96, 116-131.

Cappiello, L. Engle, R.F Sheppard, K. (2006). Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns. *Journal of Financial Econometrics*,4 (4), 537-572.

Cheung, Y. L. and Mak, S. C. (1992). A Study of the International Transmission of Stock Market Fluctuation between the Developed Markets and Asian Pacific Markets. *Applied Financial Economics*, 2, 43-47.

Chong J. and Miffre, J. (2010). Conditional Correlation and Volatility in Commodity Futures and Traditional Asset Markets. *The Journal of Alternative Investments*, 12(3), 61-75.

Choudhry, T. (1997). Stochastic Trends in Stock Prices: Evidence from Latin American Markets. *Journal of Macroeconomics*, 19(2), 285-304.

Chowdhury, A. R. (1994). Stock Market Interdependencies: Evidence from the Asia NIE's. *Journal of Macroeconomics*, 16, 629-651.

Donadelli, M. and Prosperi, L. (2012a). The Equity Risk Premium: Empirical Evidence from Emerging Markets. CASMEF Working Paper 2012/01.

Donadelli, M. and Prosperi, L. (2012b). On the Role of Liquidity in Emerging Markets Stock Prices. *Research in Economics*, 66(4), 320-348.

Donadelli, M. and Lucchetta, M. (2013). Emerging Stock Premia: Some Evidence from Industrial Stock Market Data. *Asian Economic and Financial Review*, 3(4), 398-422.

Dunis, C. L. and Shannon, G. (2004). Emerging Markets of South-East and Central Asia: Do they Still Offer a Diversification Benefits?. Working Paper, CIBEF, Liverpool John Moores University.

Engle R. (2002). Dynamic Conditional Correlation. *Journal of Business and Economic Statistics*, 20(3), 339-350.

Erb, C. B., Harvey, C. R. and Tadas, E. V. (1994). Forecasting International Equity Correlations. *Financial Analysts Journal*, 50, 32-45.

Gupta. R. and Mollik. A. T. (2008). Volatility, Time Varying Correlation and International Portfolio Diversification: An Empirical Study of Australia and Emerging Markets. *International Research Journal of Finance and Economics*, 18, 18-37.

Han, Y. (2006). Asset allocation with a high dimensional latent factor stochastic volatility model. *Review of Financial Studies*, 19(1), 237-271.

Kaplanis, E.C. (1988). Stability and Forecasting of the Co-movement Measures of International Stock Market Return. *Journal of International Money and Finance*, 7(1), 63-76.

Kasa, K. (1992). Common stochastic trends in international stock markets. *Journal of Monetary Economics*, 29(1), 95-124.

Keim, D.B. and Stambaugh, R.F. (1986). Predicting Returns in the Bond and Stock Market. *Journal of Financial Economics*, 7(2), 357-390.

Laurent, S. Rombouts, J.V.K. Violante, F. (2010). On the Forecasting Accuracy of Multivariate GARCH Models. Working Paper 10-21 CIRPEE.

Ledoit, O., Santa-Clara, P., and Wolf, M. (2003). Flexible Multivariate GARCH Modeling with an Application to International Stock Markets. *Review of Economics and Statistics*, 85, 735-747.

Longin, F. and Solnik, B. (1995). Is the correlation in International Equity Returns Constant:1960-1990?. *Journal of International Money and Finance*, 14(1), 3-26.

Markowitz, H.M. (1952). Portfolio Selection. *The Journal of Finance*, 7(1), 77-91.

Moskowitz, T.(2003). An Analysis of Covariance Risk and Pricing Anomalies. *Review of Financial Studies*, 16, 417-457.

Ng, T. H. (2002). Stock Market Linkages in South East Asia. *Asian Economic Journal*, 16(4), 353-377.

Simi, W. (2010). Strategic Asset Allocation and Markov Regime Switch with GARCH Model. Available at SSRN: http://ssrn.com/abstract=1542826.

Appendix A

A.1 Data and summary statistics

Asset Name	Code	Datatype	Frequency	Begin Date	End Date	Source
IT BENCHMARK 2 YEAR DS GOVT. INDEX	BMIT02Y(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
IT BENCHMARK 10 YEAR DS GOVT. INDEX	BMIT10Y(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
BD BENCHMARK 2 YEAR DS GOVT. INDEX	BMBD02Y(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
BD BENCHMARK 10 YEAR DS GOVT. INDEX	BMBD10Y(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
GR BENCHMARK 2 YEAR DS GOVT. INDEX	BMGR02Y(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
GR BENCHMARK 10 YEAR DS GOVT. INDEX	BMGR10Y(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
BOFA ML EMU CORP. A. 1-3Y (E)	MLEC1AE(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
BOFA ML EMU CORP. A. 7-10Y (E)	MLEC1JE(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
JPM EURO CASH 3M	JPEC3ML(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
MSCI EMU UTILITIES	M2MUU2L(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream
MSCI EMU INDUSTRIALS	M1MUIDL(RI)	TRI	Weekly	12/02/2002	04/10/2011	Datastream

Table A.1: Data Summary. Source: Datastream

Asset	Mean	StDev	ShR	Min	Max	Kurt	Skew
IT02Y	3.362	1.793	0.106	-96.825	104.100	16.839	-0.247
IT10Y	4.865	5.805	0.069	-231.808	375.490	14.775	0.664
BD02Y	3.298	1.372	0.133	-39.689	40.912	2.096	0.038
BD10Y	6.680	5.771	0.113	-141.548	157.979	1.176	0.134
GR02Y	-2.577	15.203	-0.042	-1546.986	850.033	93.677	-4.991
GR10Y	-4.167	15.153	-0.056	-1244.408	832.335	44.470	-2.686
CORP 1-3Y	3.435	1.637	0.123	-66.851	42.753	6.624	-1.243
CORP 7-10Y	3.507	5.472	0.039	-217.262	128.096	4.936	-1.177
CASH	2.830	0.202	0.581	0.479	9.802	1.991	1.212
UTIL	3.792	21.586	0.012	-652.210	1049.565	6.253	-0.304
IND	2.662	27.428	0.003	-1061.434	1340.490	6.214	-0.093

Table A.2: Summary Statistics (*full sample*). Mean, standard deviation, minimum and maximum values are annualized and expressed in percentage points. Sharpe ratio values are computed, for each asset *i*, as the ratio between the average excess return and the standard deviation, i.e. $ShR = \frac{E(R_i) - R^f}{\sigma_i}$, where R^f represents the risk-free rate. As risk-free rate proxy, we use the (weekly) one-month Treasury Bill Rate from the Kenneth R. French Data Library. The sample period goes from 12/02/2002 to 04/10/2011.

Asset	Mean	StDev	ShR	Min	Max	Kurt	Skew
IT02Y	2.795	2.630	0.043	-96.825	104.100	16.839	-0.247
IT10Y	3.998	7.766	0.036	-231.808	375.490	14.775	0.664
BD02Y	2.944	1.461	0.091	-28.354	38.827	2.096	0.038
BD10Y	9.407	6.996	0.147	-119.809	157.979	1.176	0.134
GR02Y	-16.308	27.505	-0.092	-1546.986	850.033	93.677	-4.991
GR10Y	-25.361	26.395	-0.144	-1244.408	832.335	44.470	-2.686
CORP 1-3Y	4.778	1.973	0.196	-56.668	42.753	6.624	-1.243
CORP 7-10Y	8.381	6.558	0.135	-168.646	128.096	4.936	-1.177
CASH	1.959	0.217	-0.016	0.479	9.802	1.991	1.212
UTIL	-3.396	26.859	-0.028	-596.335	1049.565	6.253	-0.304
IND	12.334	32.841	0.044	-668.625	1340.490	6.214	-0.093

Table A.3: Summary Statistics (*post-Lehman world*). Mean, standard deviation, minimum and maximum values are annualized and expressed in percentage points. Sharpe ratio values are computed, for each asset *i*, as the ratio between the average excess return and the standard deviation, i.e. $ShR = \frac{E(R_i) - R^f}{\sigma_i}$, where R^f represents the risk-free rate. As risk-free rate proxy, we use the (weekly) one-month Treasury Bill Rate from the Kenneth R. French Data Library. The sample period goes from 04/11/2008 to 04/10/2011.

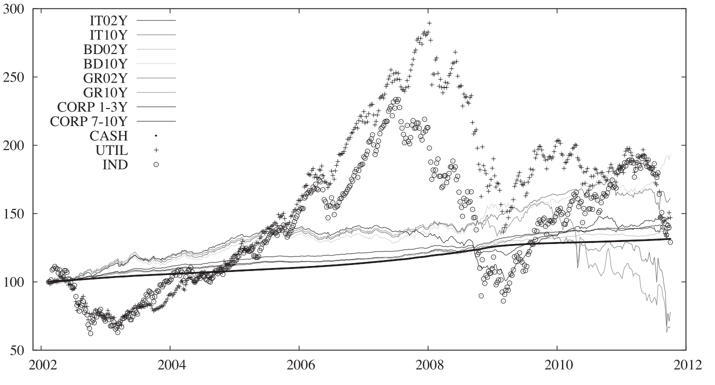


Figure A.1: This figure displays the weekly compounded performance of the 11 European securities. Performances are based on an hypothetical investment of $100 on 12/02/2002. The sample period goes from 12/02/2002 to 04/10/2011.

Appendix B
B.1 The behavior of European asset classes: some stylized facts

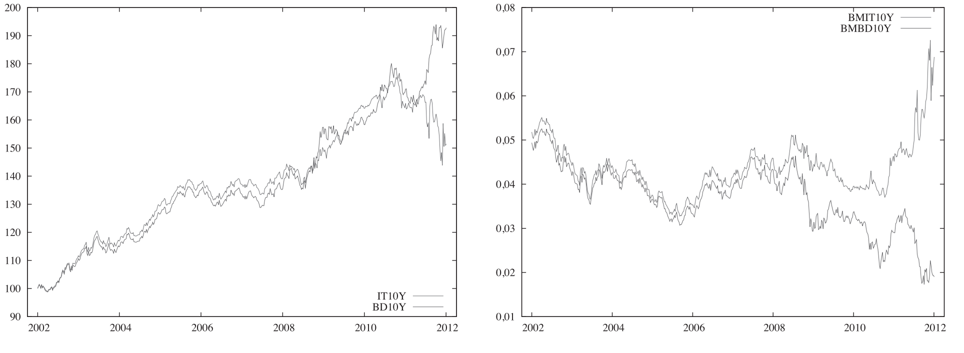


Figure B.1: Government Bond Index - Total Return (left panel) and Government Bond Index – Redemption yield (right panel). The sample period goes from 12/02/2002 to 04/10/2011.

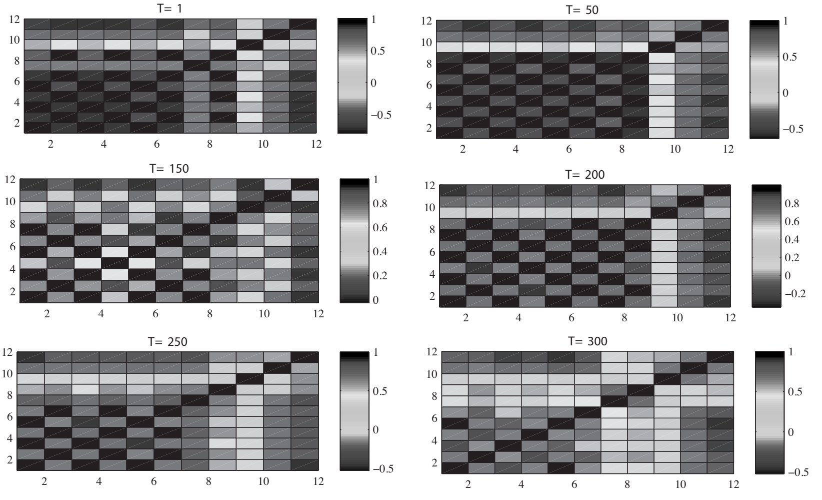


Figure B.2: Rolling Correlation Coefficients. Each correlation matrix is computed in six different windows. Each windows is composes by 60 weeks. The color scale goes from dark red to dark blue. The dark red is associated with perfect positive correlation (i.e.). The dark blue is associated with perfect negative correlation (i.e.). Assets are indexed from 2 to 12: IT 2Y=2, IT 10Y=3, BD 2Y=4, BD 10Y=5, GR 2Y=6, GR 10Y=7, CORP 1-3Y=8, CORP 7-10Y=9, CASH=10, UTILITIES=11 and INDUSTRIALS=12. The sample period goes from 12/02/2002 to 04/10/2011.

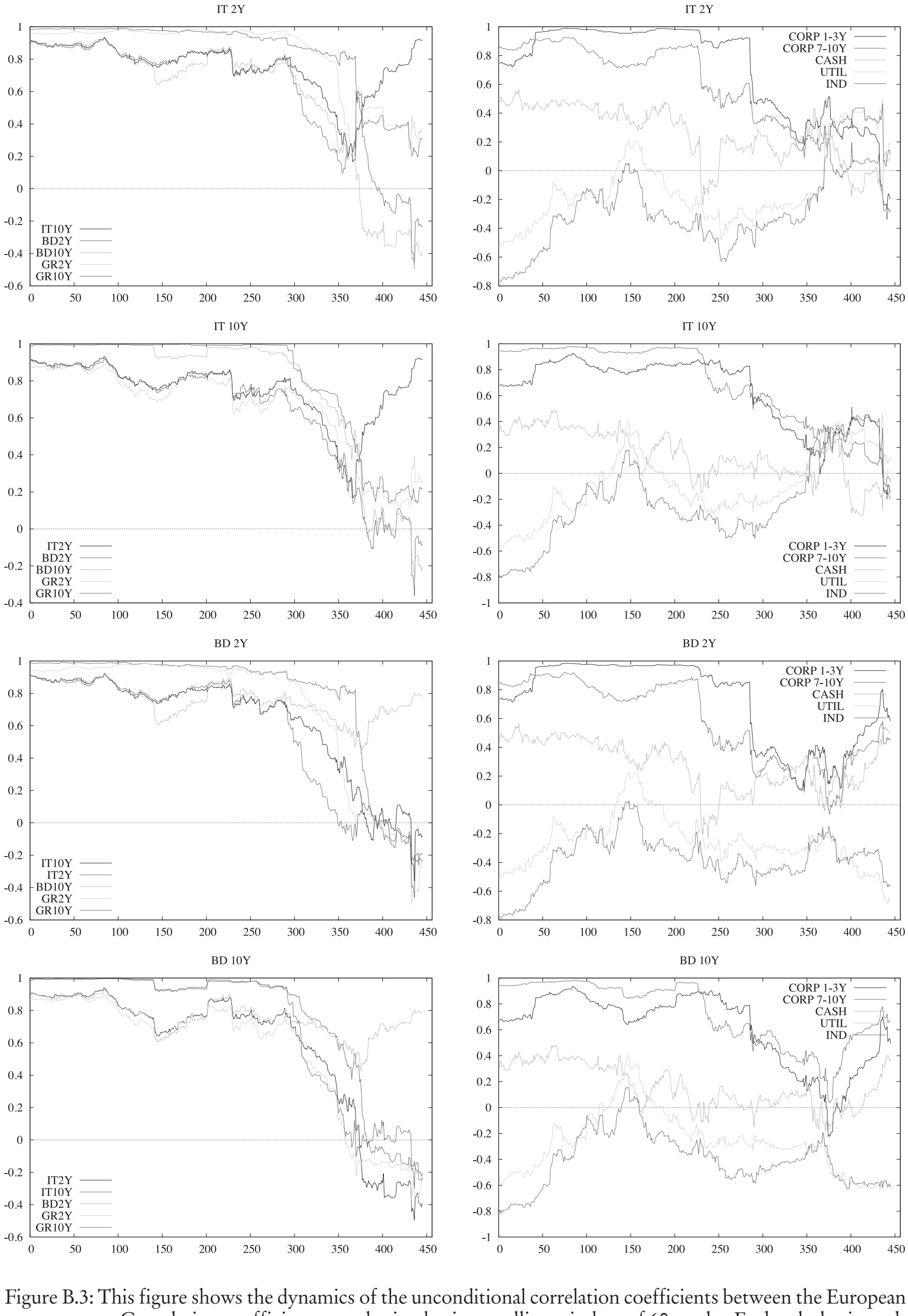


Figure B.3: This figure shows the dynamics of the unconditional correlation coefficients between the European asset returns. Correlation coefficients are obtained using a rolling window of 60 weeks. Each subplot in each row presents correlation coefficients' dynamic between a specific asset *i* and all the others. From top to bottom: IT BENCHMARK 2 YEAR DS GOVT. INDEX, IT BENCHMARK 10 YEAR DS GOVT. INDEX, BD BENCHMARK 2 YEAR DS GOVT. INDEX, BD BENCHMARK 10 YEAR DS GOVT. INDEX. The sample period goes from 12/02/2002 to 04/10/2011.

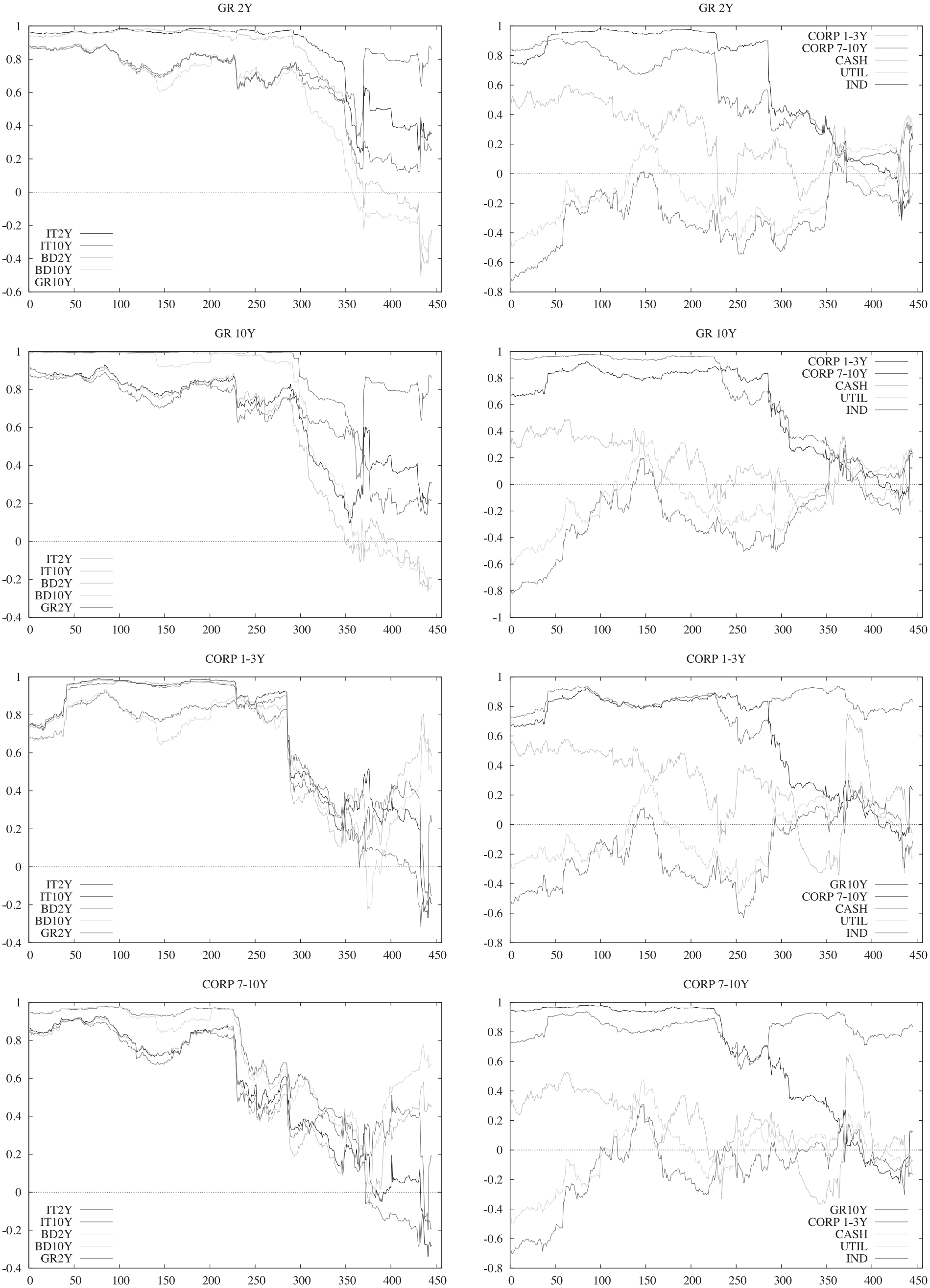


Figure B.4: This figure shows the dynamics of the unconditional correlation coefficients between the European asset returns. Correlation coefficients are obtained using a rolling window of 60 weeks. Each subplot in each row presents correlation coefficients' dynamic between a specific asset i and all the others. From top to bottom: GR BENCHMARK 2 YEAR DS GOVT. INDEX, GR BENCHMARK 10 YEAR DS GOVT. INDEX, BOFA ML EMU CORP. A. 1-3Y (E), BOFA ML EMU CORP. A. 7-10Y (E). The sample period goes from 12/02/2002 to 04/10/2011.

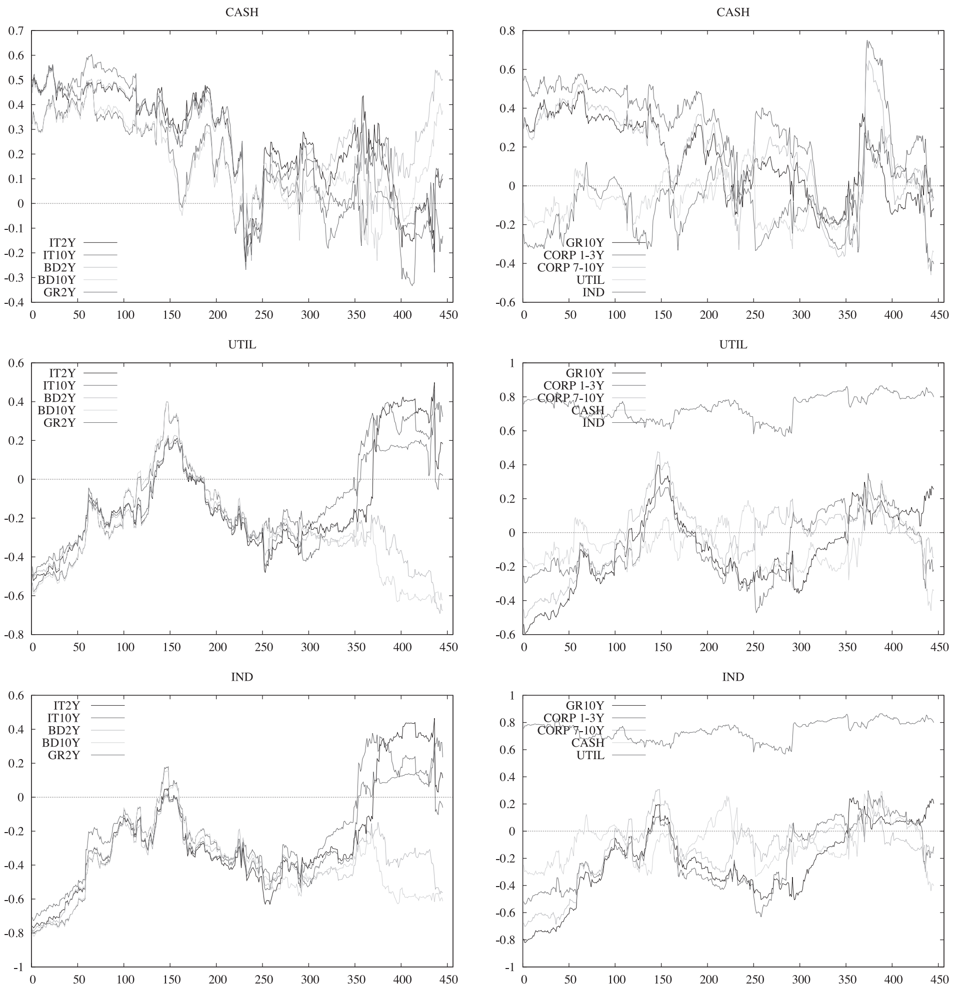
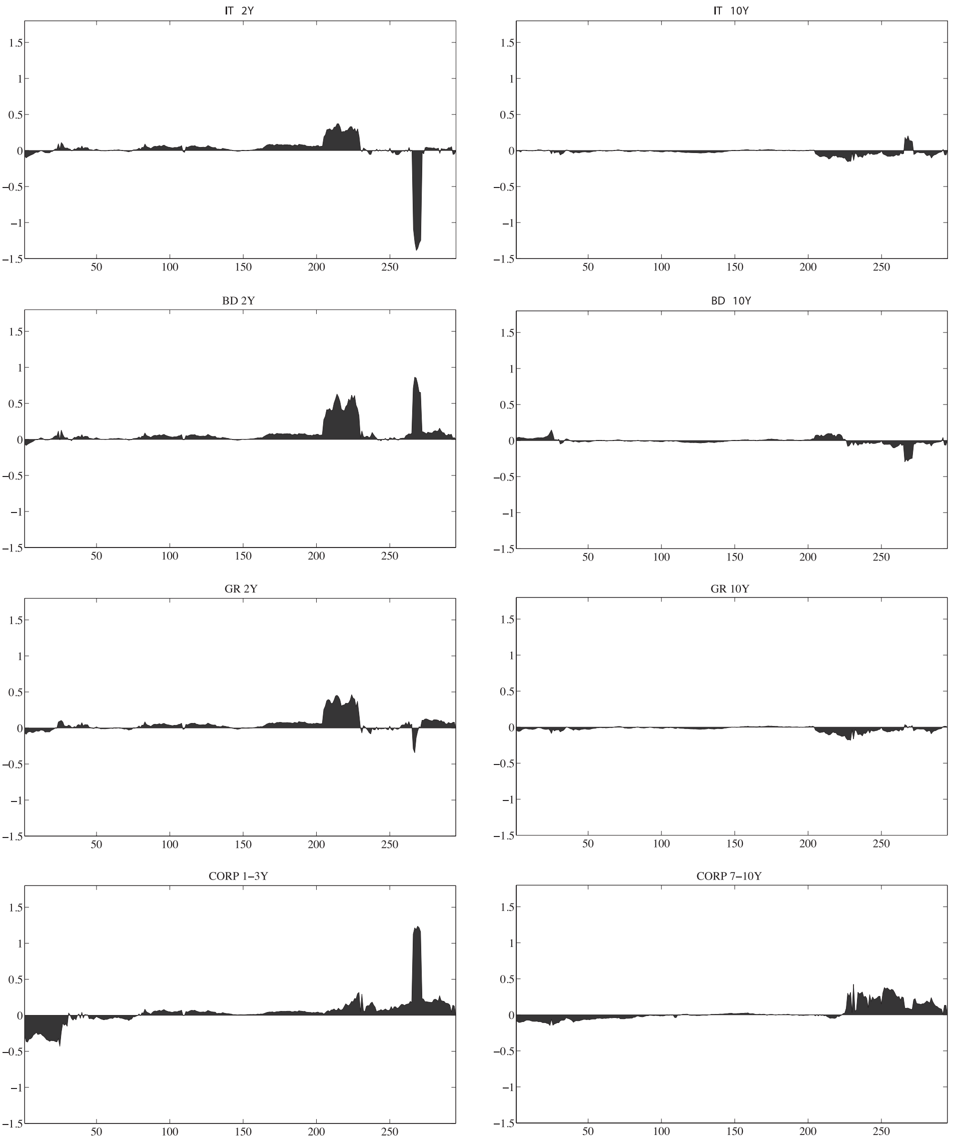


Figure B.5: This figure shows the dynamics of the unconditional correlation coefficients between the European asset returns. Correlation coefficients are obtained using a rolling window of 60 weeks. Each subplot in each row presents correlation coefficients' dynamic between a specific asset *i* and all the others. From top to bottom: JPM EURO CASH 3M, MSCI EMU UTILITIES, MSCI EMU INDUSTRIALS. The sample period goes from 12/02/2002 to 04/10/2011.

Appendix C
C.1 Ex-post dynamic MVO

Figure C.1: Rolling Portfolio Mean-Variance Optimization (*pre-crisis*). Optimal weights are computed via Eq. (5.1) using a rolling window of 60 weeks. Optimal weights sum up to one. The pre-crisis sample is composed by 355 weeks (i.e. 295 windows). The sample period goes from February 2002 (2nd week) to November 2008 (4th week).



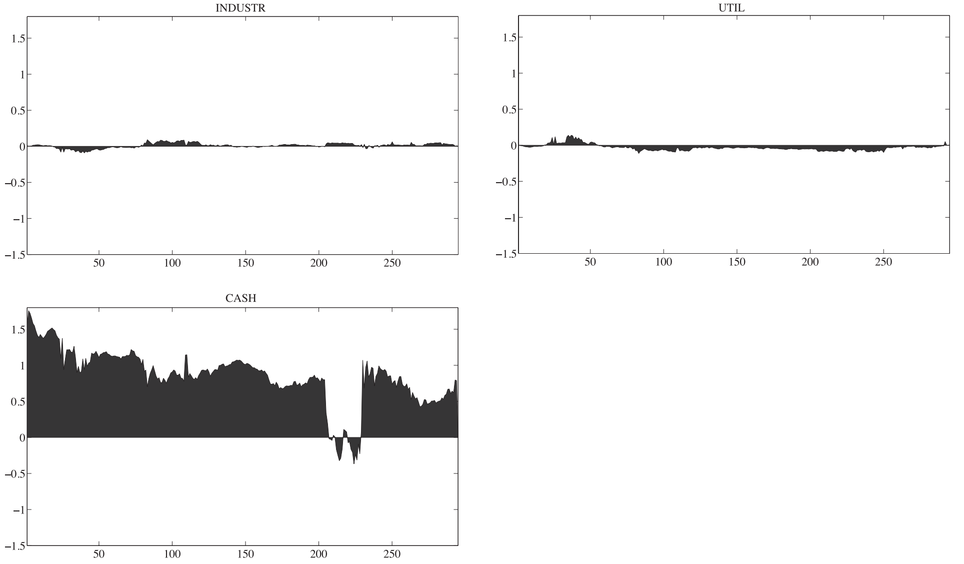
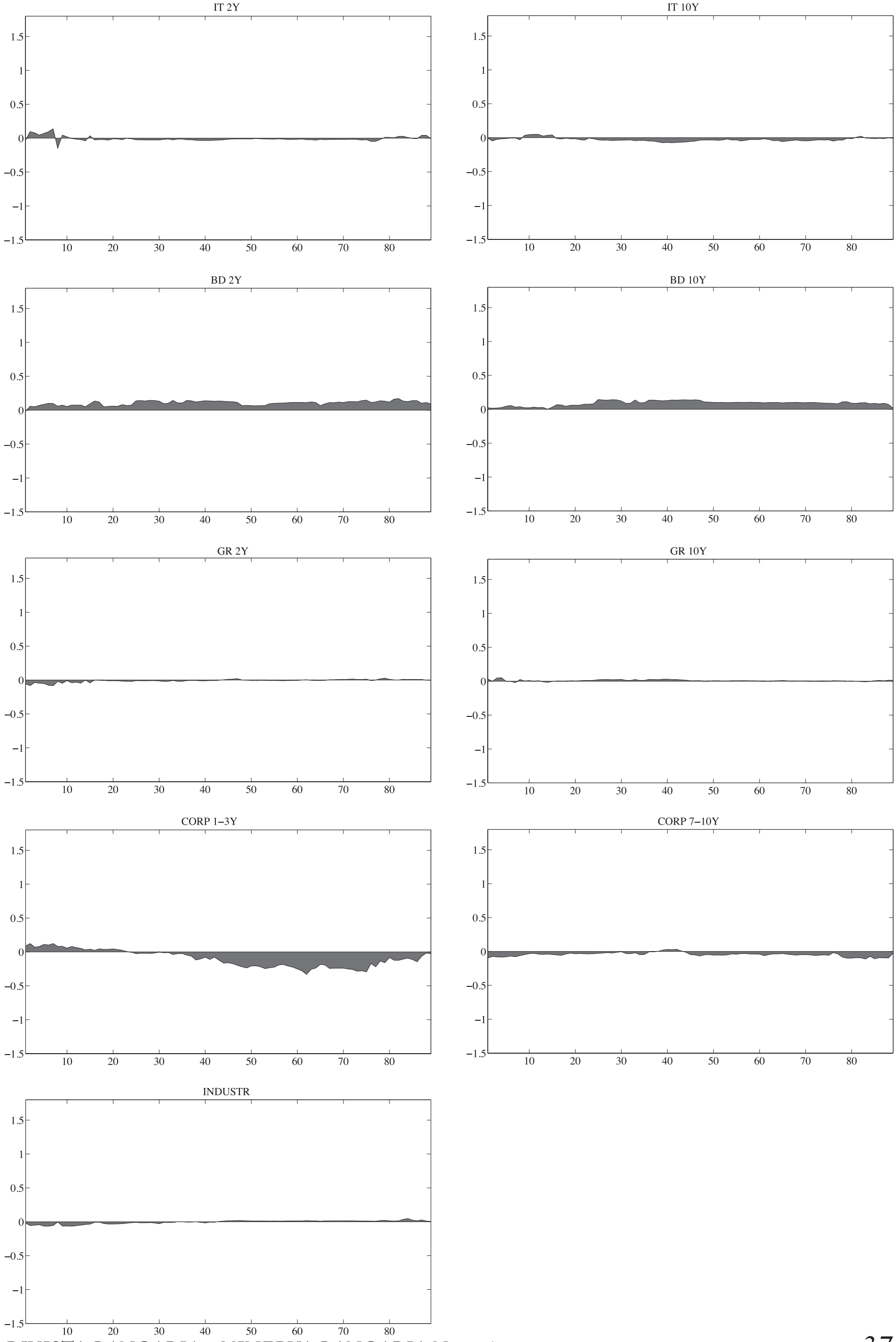

INDUSTR
UTIL
CASH
1.5
1
0.5
0
−0.5
−1
−1.5
50
100
150
200
250

Figure C.2: Rolling Portfolio Mean-Variance Optimization (*post-crisis*). Optimal weights are computed via Eq. (5.1) using a rolling window of 60 weeks. Optimal weights sum up to one. The post-crisis sample is formed by 149 weeks (i.e. 89 windows). The sample period goes from December 2008 (1st week) to October 2011 (1st week).



Appendix D
D.1 The dynamic conditional correlation coefficients

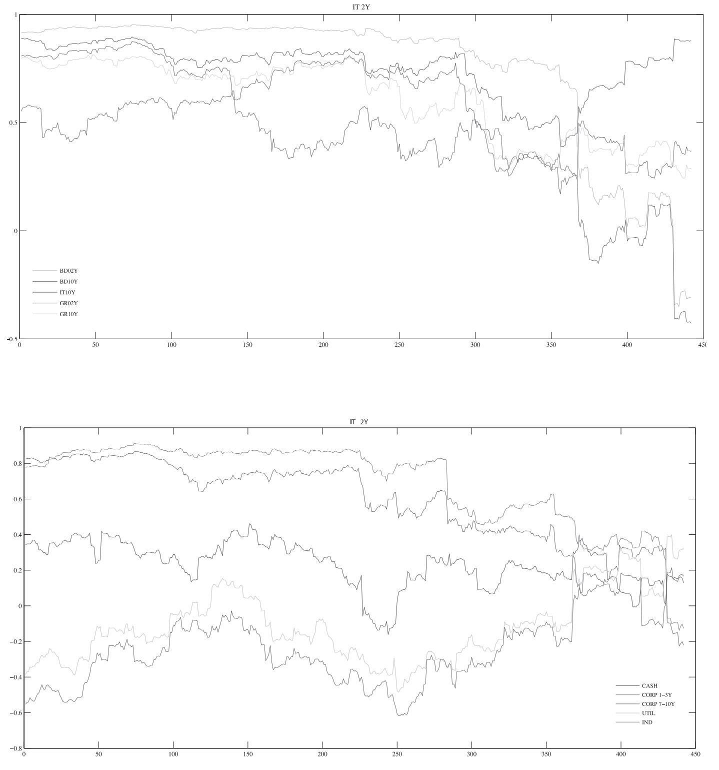
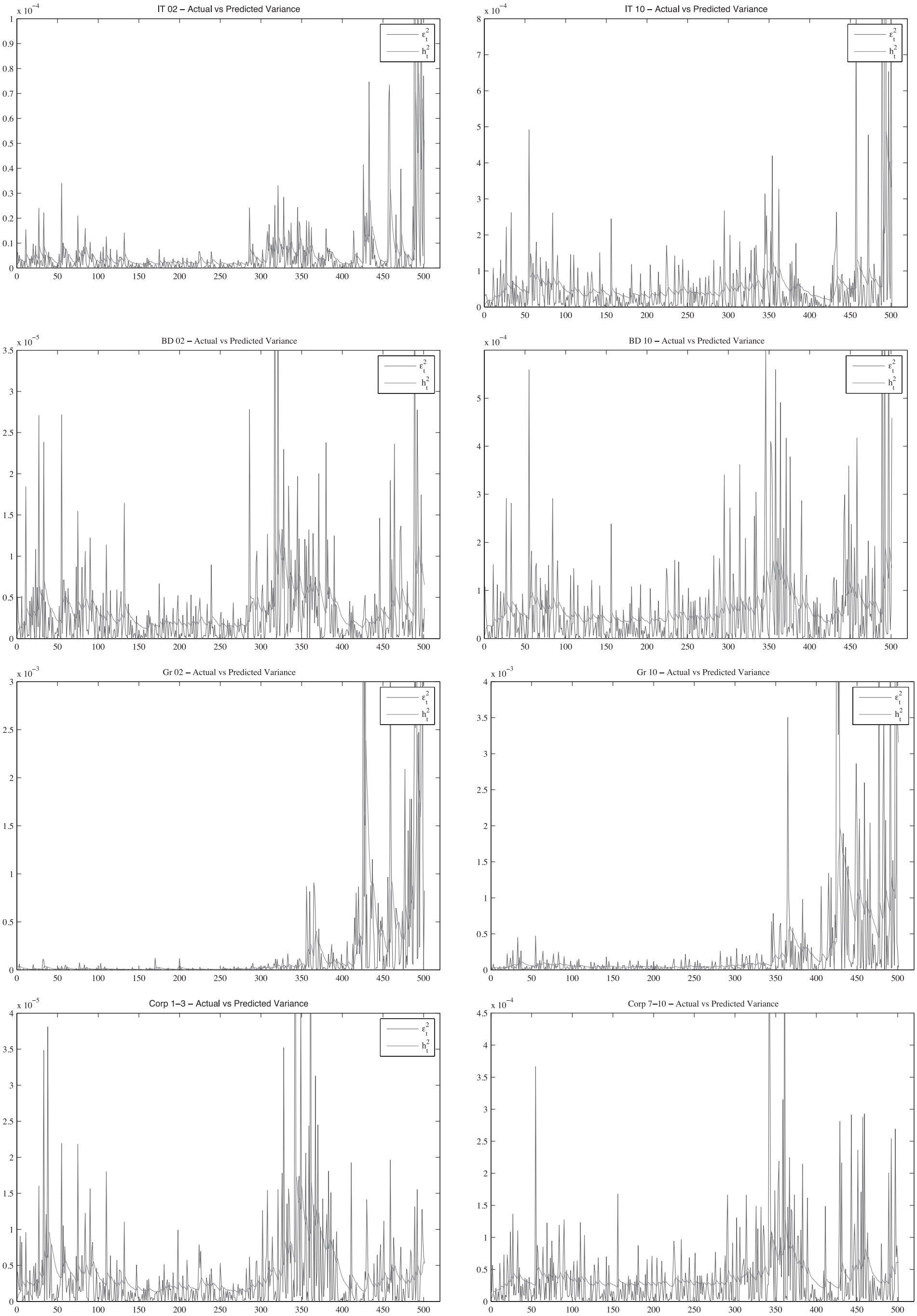
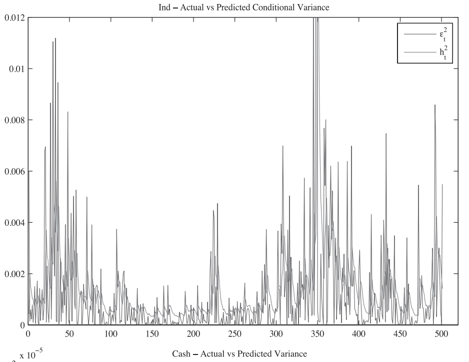
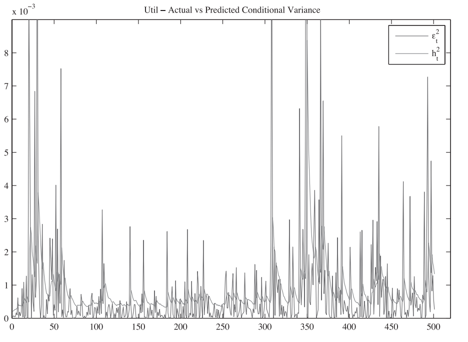


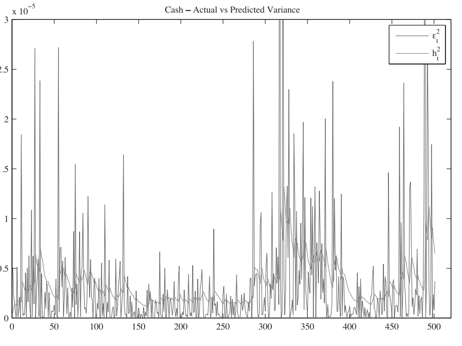
Figure D.1: This figure shows the dynamics of the conditional correlation coefficients between the European asset returns. Conditional correlation are estimated in a GARCH context. The Italian IT 2Y Bond is used as benchmark. The sample period goes from 12/02/2002 to 04/10/2011.

Figure D.2: MGARCH: Actual vs Predicted Conditional Variance. The blue and the green lines represent the squared of the VAR's residuals and the corresponding estimated element of the matrix , respectively. The sample period goes from 12/02/2002 to 04/10/2011.




Ind – Actual vs Predicted Conditional Variance
ε_t^2
h_t^2

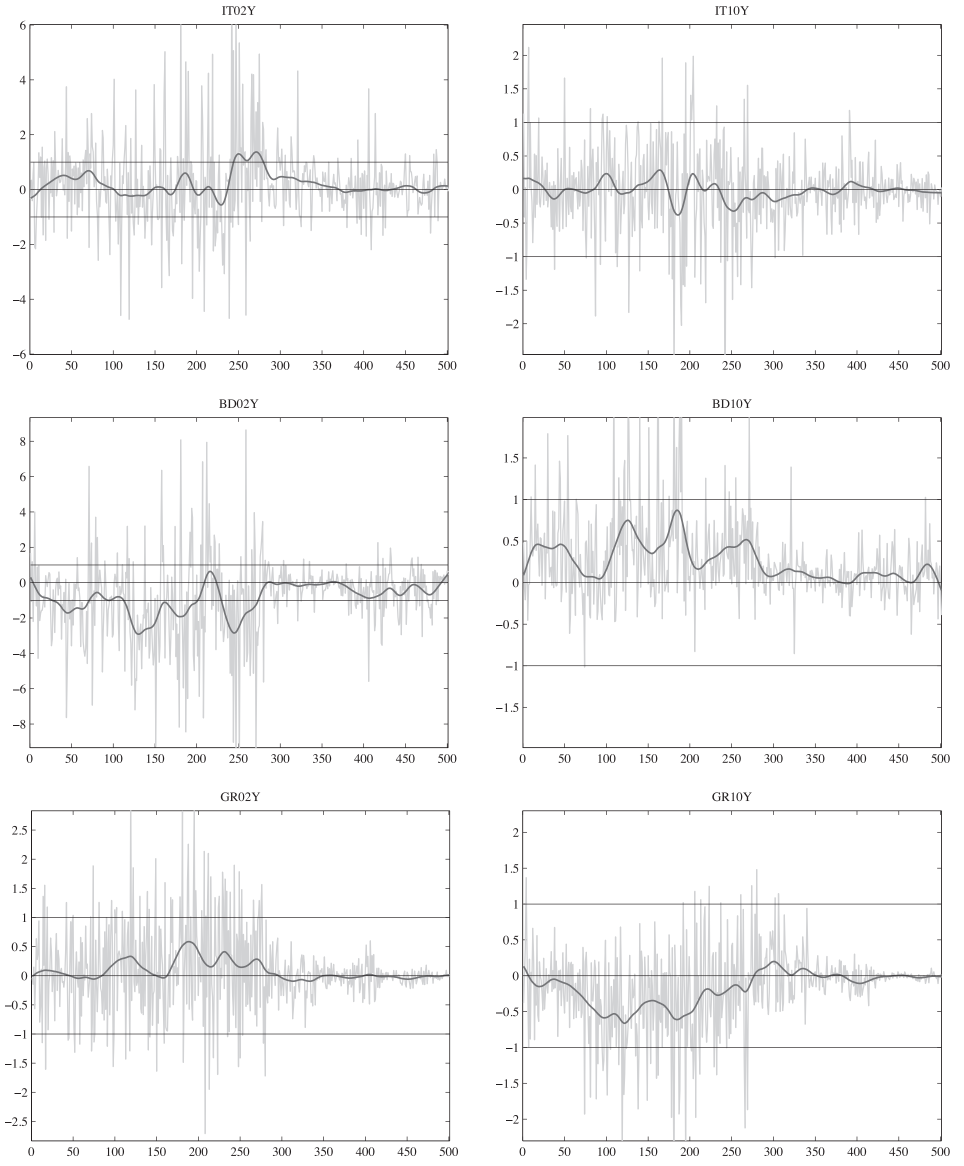

Util – Actual vs Predicted Conditional Variance
x 10^−3
ε_t^2
h_t^2

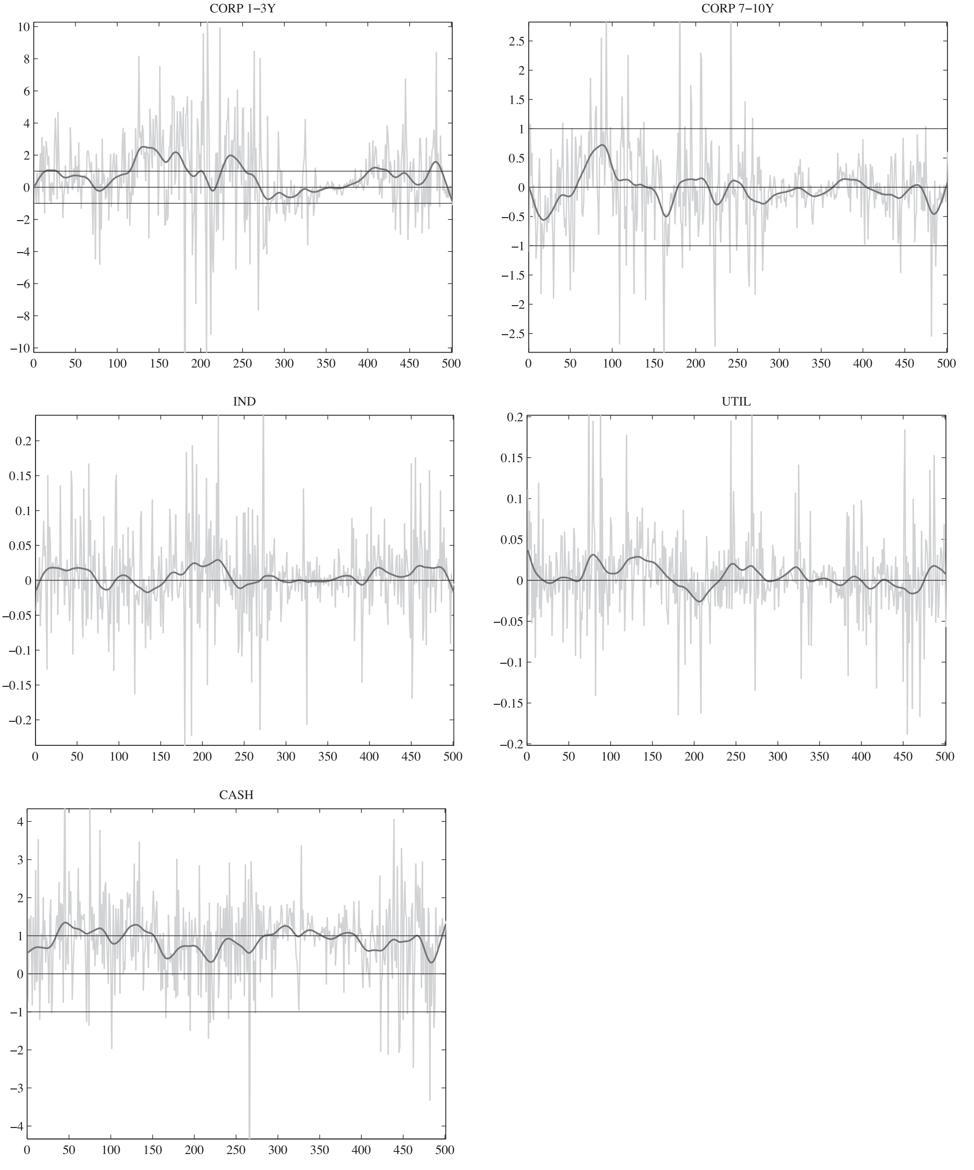

Cash – Actual vs Predicted Variance
x 10^−5
ε_t^2
h_t^2

Appendix E

E.1 Ex-ante dynamic MVO

Figure E.1: MGARCH - Optimal Portfolio Allocation. The gray bars represent optimal weights at date *t*. The optimal allocation is computed via a standard MVO approach. The one-period ahead expected returns and variances are computed using the VAR(2) and the DCC-GARCH, respectively. The red line represents the Hodrick-Prescott filter of the dynamic allocations. The sample period goes from 12/02/2002 to 04/10/2011.

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