In search of the determinants of European asset market comovements*

Pedro Gomes† and Abderrahim Taamouti‡

April 28, 2016

ABSTRACT

We show, in a broad class of affine general equilibrium models with long-run risk, that the covariances between asset returns are linear functions of risk factors. We use a dynamic conditional correlation model to measure the covariances of stock and sovereign bond markets in the Euro Area. We use a new approach to measure risk factors based on *Google search data*. The factors explain 50 to 60 percent of the variation of the covariances between European stocks and 25 to 35 percent of the covariances between European bonds. The information improves the portfolio performance compared to an equally weighted portfolio.

JEL Classification: C22, G12, G15, G17, E44.

Keywords: Stock and bond comovements; affine general equilibrium models; Eurozone crisis; Google Trends; portfolio weights modeling.

*The authors thank three anonymous referees and the Editor Prof. Hamid Beladi for several useful comments. Financial support from the Spanish Ministry of Education through grants #ECO2010-19357, MDM 2014-0431 and the Comunidad de Madrid, MadEco-CM (S2015/HUM-3444) are also acknowledged.

†Corresponding author. Universidad Carlos III de Madrid, Department of Economics. Address: Calle Madrid 126, 28903 Getafe, Spain. Tel: +34 91 624 5732; e-mail: pgomes@eco.uc3m.es

‡Durham University Business School, Department of Economics and Finance. Address: Mill Hill Lane, Durham, DH1 3LB, United Kingdom. Tel: +44 191 334 5423; e-mail: abderrahim.taamouti@durham.ac.uk.

1 Introduction

The stylized facts that characterize the comovement of international asset markets are of great importance to economists, policymakers, and investors. These facts help economists grasp the links between the real economy and finance. They inform policymakers on how markets react to international shocks and how to design reforms of the financial system. They advise investors on how to improve risk management and increase their returns through the diversification of their portfolios.

Several theoretical studies have studied the comovement between asset returns. Beltratti and Shiller (1992) use a present value model to calculate the theoretical correlation between stock and bond markets. They find that the discount rate has opposite effects on stocks and bonds. Ammer and Mei (1996) add a foreign stock return to the model and characterize the covariance between international stocks. In their application, they find that the covariance between national indices is driven by a common stock risk premia rather than by the comovement in fundamental variables. D'Addona and Kind (2006) set an affine asset pricing model and derive a formula for the stock-bond correlation determined by the dynamics of inflation and the dividend-yield ratio. Campbell *et al.* (2013) consider a quadratic, rather than affine, pricing model in which the nominal term structure of interest rates is driven by the real interest rate, risk aversion, temporary and permanent components of expected inflation, and the covariance between nominal variables and the real economy. The model features a changing covariance of bond and stock returns, and helps produce negative comovements between them. Barsky (1989) builds a general equilibrium model and shows that the relationship between stocks and bonds depends on the degree of aversion, the intertemporal substitution, and the share of the corporate sector in total wealth.

We add to this literature by characterizing the asset market comovement in a recent class of affine general equilibrium models with long-run risk. These models introduce small but persistent stochastic components in the mean and variance of consumption growth, which together with Epstein–Zin preferences, successfully match several stylized facts in finance such as equity premium, risk-free rate, market return volatility, and price-dividend ratio [see Bansal and Yaron (2004)]. Our main theoretical contribution is to show that, under some general conditions, the covariance between the returns of any two assets (stocks, bonds) is a linear function of latent risk factors. Although this result is not surprising given the class of models, it has not yet been formalized in the literature. The implication for the empirical exercise is that, if measures of covariances and the risk factors are available, we can use simple linear regression techniques to predict the assets' covariance.

This result raises a challenge: both sides of the regression are unobservable. For the left hand side, we use Engle's (2002) dynamic conditional correlation (DCC) model to filter the covariances. It is common in the empirical literature to use parametric methods to filter the covariance between assets. Using correlations, filtered from a multivariate generalized autoregressive conditional heteroskedasticity (GARCH) model, between the monthly asset excess returns of seven major countries from 1960 to 1990, Longin and Solnik (1995) find that correlations increase with conditional volatility and interest rate and decrease with dividend yields. More recently, Hunter and Simon (2005) use a bivariate GARCH framework to examine the lead-lag relationships and the conditional correlations between 10-year US government bond returns and their counterparts from the United Kingdom, Germany, and Japan. The DCC model that we consider has the flexibility of univariate GARCH models without the computational difficulties of multivariate GARCH models. For a robustness check, we also use nonparametric measures of covariances as in Solnik *et al.* (1996).

For the right hand side of regression, several studies use *predetermined* variables to explain the comovement between asset returns. For example, von Furstenberg and Jeon (1989) use interest rate differentials, exchange rates, and prices of oil and gold. Campbell and Ammer (1993) use dividends, inflation, short-term real interest rates, and excess stock and bond returns. D'Addona and Kind (2006) and Beltratti and Shiller (1992) use inflation and the dividend-yield ratio. Alternatively, other studies use econometric factor models to extract the latent variables. King *et al.* (1994) use 16 national stock markets and a multivariate factor model in which the volatility of returns is induced by changing volatility in the orthogonal factors. They find that only a small proportion of the time variation in the covariances between national stock markets can be accounted for by observable economic variables. Baele *et al.* (2010) use a dynamic factor model in which the coefficients depend on sudden regime changes. They find that macroeconomic fundamentals contribute little to explaining stock and bond return correlations whereas other factors, especially liquidity proxies, play a more important role. We follow this latter literature that uses factor analysis and we extract a number of factors from a large set of data using principal component analysis.

The empirical literature also differs on the frequency of the data. Studies focusing on financial variables generally use weekly data, such as in Clare and Lekkos (2000) and Solnik *et al.* (1996), or daily data, such as in von Furstenberg and Jeon (1989). In general, studies that focus on economic determinants use yearly, as in Beltratti and Shiller (1992), quarterly as in Baele *et al.* (2010) and Campbell *et al.* (2013), or monthly data, such as in Campbell and Ammer (1993). The literature has found two ways to address the clear mismatch between the frequency of financial and economic data. On the one hand, there are event studies, such as that by Karolyi *et al.* (1996), which investigate how US macroeconomic announcements affect the correlation between Japanese and US stocks using daily data from 1988 to 1992. Other researchers have used Mixed-data sampling methods (MIDAS), as in Ghysels *et al.* (2006), Ghysels *et al.* (2007). One example is Engle *et al.* (2013) that analyses the relation between stock market volatility and macroeconomic activity since the 19th century, distinguishing short-run from secular movements. They use the MIDAS approach to link the monthly, quarterly, or bi-annual macroeconomic variables to the secular component and a mean reverting daily GARCH process for the short-run movements. They find that at a daily level, inflation and industrial production growth, account for between 10 % and 35 % of one-day ahead volatility prediction.

Our second main contribution is to use a novel type of data based on *Google* keyword searches to address the mismatch of the frequency of economic and financial data. *Google* designed an application, *Google Trends*, which provides indexes of how many times people have "Googled" a specific word or combination of words relative to overall traffic. These indexes have been available at a weekly frequency since 2004 for individual countries.

Choi and Varian (2012) were the first to claim that *Google Trends* data predict several aspects of the current economic activity. Since then, researchers have used these data to forecast labor markets, housing markets, the automobile sector, inflation expectations, or private consumption. Askitas and Zimmermann (2009), D'Amuri (2009), D'Amuri and Marcucci (2010), and Choi and Varian (2009) demonstrate the power of internet job-search indicators to predict unemployment rate or the initial claims of unemployment benefits in the United States and Germany. Vosen and Schmidt (2011) construct an indicator for private consumption and claim it is superior to the common survey-based indicators such as the University of Michigan Consumer Sentiment Index. Similar results were reported in Kholodolin *et al.* (2010) and Della-Penna and Huang (2009). Guzman (2010) proposes a measure of real-time inflation expectations based on *Google* search data, comparing it with 37 indicators of inflation expectations. The indicator anticipates the inflation rate by 12 months and has the lowest forecast error. Wu and Brynjolfsson (2013) find that a housing search index predicts future housing market sales and prices; central banks also use these data. McLaren and Shanbhogue (2011) predict changes in unemployment rate and housing prices in the United Kingdom. Carrière-Swallow and Labbé (2013) find that the internet search index of automobiles improves the fit of models of automobile sales in Chile. Suhoy (2009) improves the unemployment forecast in Israel. In other fields, internet search data has been used to detect influenza epidemics [Ginsberg *et al.* (2009)].

These data are available at a weekly frequency for different countries, which provides possible applications to the finance literature. Da *et al.* (2011) were the first to do so. They use the keyword search of the code name of specific stocks to construct a measure of investor attention, which is correlated with other proxies of investor attention but is available in a more timely fashion. They find that increases in the measure predicts higher stock prices in the following two weeks and an eventual price reversal within the year. Latoeiro *et al.* (2013) use a similar strategy to predict stock market activity of European stocks. They find that an increase in the searches for stocks is followed by a temporary increase in volatility and volume and a drop in cumulative returns.

Our contribution is to link these two strands of the literature. As the *Google* search indicators relate to economic fundamentals but are available at a weekly frequency, we can connect them to certain properties of financial markets. We can explore the data comparability across countries and avoid the use of economic data, which are only available with time-lags at a quarterly or monthly frequency.

In the empirical application, we predict the covariances between asset returns in four euro area countries: Germany, France, Italy, and Spain. We analyze the stock and sovereign bond markets, before and during the Eurozone crisis, when the variation in market covariances became more pronounced. While this sample is of great interest for economists and policymakers, few studies focus on it. Perego and Vermeulen (2013) study the macroeconomic determinants of European stock and bond market correlation between 1999 and 2012. Tamakoshi *et al.* (2012) focuses on the correlation of Greek stock market returns with those of six other Euro Area countries during the crisis. Kenourgios and Samitas (2009) study the correlation of both equity and bond markets of Euro Area and new accession countries, on the decade prior to the crisis.

We use the DCC model to filter the weekly covariances in the Euro Area. We select 10 indicators from *Google Trends* related with economic activity for the United States and the four European countries. For each country, we extract a number of factors with principal component analysis. These factors are correlated with several monthly macroeconomic indicators for all countries, particularly with changes in unemployment rate, inflation, or the growth rate of industrial production. All factors exhibit a clear cyclical pattern. We consider the US factors as global and the orthogonalized European ones as country specific. We regress the different measures of covariance on these factors.

The factors extracted from *Google* search data predict the comovement in cross-country European stock and sovereign bond markets. They explain 50 to 60 percent of the variation of the covariance of stock market returns and 25 to 35 percent of the variation of bond market returns. While the comovement of European stock markets is mainly due to global factors, the country-specific ones are more important in the dynamics of the sovereign bond market. In all regressions, a deterioration of economic activity in the United States raises the covariance within European bond and stock markets. Furthermore, we find that the comovement between stock and bond returns within the same European country is again dominated by the global factors. Interestingly and as opposed to the results obtained for cross-country stock and bond comovement, it seems that all the different dimensions of a US recession decrease the covariance between stock and bond markets of same European country.

Our third and final contribution is to measure the financial gains for investors of using the information in *Google* search data. The aforementioned literature does not evaluate how the determinants of the comovement of assets can improve portfolio diversification. One notable exception is the study by Ang and Bekaert (2002), which sets up a general asset allocation problem with regime switching capturing asymmetric correlation. They evaluate the financial gains of considering asymmetric correlation between international equities instead of a symmetric one. We use a portfolio selection approach to examine the implications of time-varying covariances between international stock and bond returns for asset allocation and risk management. Following Brandt *et al.* (2009) and Bouaddi and Taamouti (2013), our approach consists of directly modeling portfolio weights as a function of the global factors. The empirical results indicate that most of the global factors have a statistically significant effect on portfolio weights. Furthermore, the portfolio with time-varying weights outperforms an equally weighted portfolio or a portfolio with constant weights, in mean returns and Sharpe ratios, both in- and out-of-sample. Part of the gains are due to the weekly frequency of the portfolio adjustment.

The rest of the paper is organized as follows. Section 2 provides the theoretical model underpinning the asset returns' comovement. Section 3 describes the data and measures of covariances between asset returns, extracts the risk factors using Google search data, and shows their correlation with economic activity. Sections 4 and 5 report how the covariances depend on the global and country-specific factors. Section 6 examines the implications for international portfolio allocation and risk management. Section 7 presents the conclusions. Proofs and additional results appear in Appendices A to E.

2 The theoretical relationship between international asset market returns

This section motivates the empirical analysis performed in the paper. In particular, we provide a justification for the use of linear regression models to explain the international asset market comovements as an affine function of the variables underlying the state of the economy (hereafter state variables). We show that this affine relationship between the state variables and the covariance between international asset returns is an implication of the affine general equilibrium models described in Duffie *et al.* (2000), Eraker (2008), and Feunou *et al.* (2014). These models can be interpreted in terms of long-run risk models introduced by Bansel and Yaron (2004) and match several stylized facts in finance. Focusing on two countries, Colacito and Croce (2010, 2013) have recently consider similar type of models to show the welfare gains of financial integration that are related to risk sharing, and to document that both the anomaly of low correlation between consumption differentials and exchange rates, and the forward-premium anomaly, have become more severe over time.

Let us denote $r_{t+1}^{a_1} = \left(r_{t+1,1}^{a_1}, ..., r_{t+1,n}^{a_1}\right)^\top$ and $r_{t+1}^{a_2} = \left(r_{t+1,1}^{a_2}, ..., r_{t+1,n}^{a_2}\right)^\top$ the vectors of asset returns a_1 and a_2 in n countries, respectively. Asset returns a_1 and a_2 could be given by equity and/or bond returns. We consider an economy with K state variables, X_t, and with the following properties: (i) the joint distribution of $\left(r_{t+1}^{a_1}, r_{t+1}^{a_2}\right)$ and X_t belongs to the family of affine jump-diffusion continuous-time (or discretized) models (Duffie *et al.*, 2000); and (ii) the stochastic discount factor is an exponential affine function of X_t and $\left(r_{t+1}^{a_1}, r_{t+1}^{a_2}\right)$ (Gourieroux and Monfort, 2007; Christoffersen *et al.*, 2010). Feunou *et al.* (2014) formalize these properties and shows that this class of models nests a wide array of discrete-time asset-pricing models. Indeed, the affine long-run risk models with Epstein–Zin–Weil preferences (Bansal and Yaron, 2004; Eraker, 2008) also fit this description.

In the context of the above class of models, we show (see Appendix A) that the covariance between the vectors of international asset returns (equity and /or bonds), $r_{t+1}^{a_1}$ and $r_{t+1}^{a_2}$, are given by:

$$E_t\left[r_{t+1}^{a_1}\left(r_{t+1}^{a_2}\right)^\top\right] = \beta_{a_1,a_2,0} + X_t^\top \otimes \beta_{a_1,a_2,X}, \tag{1}$$

where "⊗" is the Kronecker product, and $\beta_{a_1,a_2,0}$ and $\beta_{a_1,a_2,X}$ are the intercept and slope coefficients. Equation (1) states that the covariance between any two assets is given by a linear function of the state variables X_t. This result motivates the specification used in Section 4. One limitation of this approach is that it does not provide a direct link between the unobserved state variables and specific economic variables. While some people associate them with predetermined variables such as unemployment rate or inflation, we opt to extract them from a large set of data.

3 Data description

3.1 Stock and bond market returns and covariances

Our empirical analysis covers four European countries (France, Germany, Italy, and Spain) along with the United States. The weekly dataset runs from January 2002 to October 2011. Data for the sovereign bond yields, which is for the 10-year government bond end-of-day data are obtained from Reuters, and the stock market data is obtained from an equity index reported in Datastream.

We define the weekly stock market return $r^s_{i,t}$ at week t for country i as the difference in log prices of the equity index on the Friday from the previous week, and we define the bond market return $r^b_{i,t}$ as the difference in log yield at the previous Friday from the following week. We use two different approaches to measure the ex-post time-varying covariances between international stock and bond returns: **(i)** the DCC model and **(ii)** a nonparametric approach by computing a rolling pairwise covariance of weekly returns.

Proposed by Engle (2002) to capture the dynamics in correlation, the DCC model is becoming a benchmark model for multivariate specifications. The DCC has the flexibility of univariate GARCH models, but it still provides parsimonious correlation specifications without the computational difficulties of multivariate GARCH models. Further, this model allows for the conditional correlations (covariances) to evolve according to a GARCH-type structure. In these, the number of parameters in the conditional correlation model can be limited by using the idea of "correlation targeting," which means that the unconditional correlations implied by the model are restricted to be equal to the unconditional sample correlations. For a bivariate process, the GARCH(1,1)-type specification of conditional correlation coefficient between the return of an asset in country i and the return of another asset in country j, say $\rho_{i,j,t+1}$, is given by

$$\rho_{i,j,t+1} = Corr\left(r_{i,t+1}, r_{j,t+1}\right) = \frac{q_{ij,t+1}}{\sqrt{q_{ii,t+1}\ q_{jj,t+1}}}, \tag{2}$$

where the auxiliary variable $q_{ij,t+1}$ is defined by

$$q_{ij,t+1} = \overline{\rho}_{ij} + \lambda_1\left(z_{i,t}z_{j,t} - \overline{\rho}_{ij}\right) + \lambda_2\left(q_{ij,t} - \overline{\rho}_{ij}\right), \tag{3}$$

and in turn, where $z_{i,t}$ and $z_{j,t}$ are the normalized return innovations, and $\overline{\rho}_{ij}$ is the unconditional expectation of the cross-product of return innovations between the asset return in country i and that in country j. While $q_{ij,t+1}$ is not explicitly the covariance, it can be interpreted as the covariance dynamics.

Appendix B.1 reports the estimated coefficients of the GARCH model and the DCC model in Equation 3. The GARCH coefficients estimates are positive and statistically significant for both stock and bond returns across the different pairs of countries. The high values (close to one) of the GARCH coefficient estimates indicate that volatilities are persistent. The estimated coefficients of the DCC model, λ_1 and λ_2, are positive for stocks and bonds across all countries. The estimates of λ_1 are statistically significant in most of the cases, whereas the estimates of λ_2 are always significant. The high values of λ_2 indicate a high persistence in correlation. The graphs of the estimated dynamic covariances and correlations can be found in Appendix B.2.

We also estimate nonparametrically the covariances between any two assets. We use an arithmetic equally weighted estimator (hereafter moving average estimator). For a sample of returns $\{r_{i,t},\ r_{j,t}\}_{t=1}^{T}$, the moving average estimator of covariances between the returns in country i and in country j, say $q_{ij,t+1}$, is given by the following formula:

$$q_{ij,t+1} = \frac{1}{m} \sum_{\tau=t-m}^{t} \left(r_{i,\tau} - \bar{r}_{i,t+1}\right)\left(r_{j,\tau} - \bar{r}_{j,t+1}\right) \tag{4}$$

where

$$\bar{r}_{h,t+1} = \frac{1}{m} \sum_{\tau=t-m}^{t} r_{h,\tau}, \text{ for } h = i, j.$$

In the empirical application, we take $m = 20$ weeks. Furthermore, the nonparametric estimator of correlations between two assets, say $\rho_{ij,t+1}$, is given by the following formula:

$$\rho_{ij,t+1} = \frac{\sum_{\tau=t-m}^{t} \left(r_{i,\tau} - \bar{r}_{i,t+1}\right)\left(r_{j,\tau} - \bar{r}_{j,t+1}\right)}{\sqrt{\left(\sum_{\tau=t-m}^{t} \left(r_{i,\tau} - \bar{r}_{i,t+1}\right)^2\right)\left(\sum_{\tau=t-m}^{t} \left(r_{j,\tau} - \bar{r}_{j,t+1}\right)^2\right)}}. \tag{5}$$

3.2 Measurement of international risk factors: Google Trends

To extract the international risk factors, we use a novel type of data based on internet keyword search, provided by *Google Trends*. The data consist of indexes that reflect how many times people have "Googled" a specific word or combination of words, relative to overall traffic. These indexes are available at a weekly frequency since 2004 by country. Usually, the data is available up to the previous week. *Google Trends* also provides compound indexes of specific categories. As explained in the introduction, several studies have shown that these indexes are good predictors of key economic indicators such as unemployment rate, private consumption, or real-time inflation expectations.

The data from *Google Trends*, which are available at a weekly frequency, enables the connection between economic and financial data. In reality, the joint movement of stock and sovereign bond markets is driven by macroeconomic factors: unemployment, investment, private consumption, inflation, government spending, taxation, and so forth. These data are only available at a quarterly frequency or, for some variables, at a monthly frequency. To use them, one must average the financial data and lose a significant fraction of their variation. The use of the internet search data that are correlated to the evolution of macroeconomic aggregates allows us to overcome this obstacle.

To extract the factors, we proceed in the following way. First, for each of the countries under consideration, we get 10 indexes related to several dimensions of economic activity: *economic news, jobs, fiscal policy news, credit and lending, manufacturing, industrial materials equipment, construction and maintenance, property, currency and foreign exchange, and the automobile industry.* These indexes are constructed based on searches of related words. Appendix C.1 shows the most important keywords for each index in each country. The indexes are available since the first week of 2004. There are strong elements of seasonality that we removed using a ratio-to-moving average method. We use the indexes in logs. An augmented Dickey-Fuller test for unit root indicates that the indexes are stationary around a deterministic trend, so we remove it to get a stationary time series. Thereafter, for each country, we carry out principal component analysis and extract the factors associated with eigenvalues greater than 1. They are considered practically significant because they explain an important amount of the variability in the data, while those with eigenvalues less than 1 are practically insignificant. Appendix C.2 shows the 10 indexes for the United States and the extracted factors for all countries.

Table 1 summarizes the number of selected factors and the percentage of the variance explained. The selected factors (eigenvalues greater than 1) explain more than two thirds of the variability of the data in all countries. Following Ludvigson and Ng (2009), we quantify the relationship between the estimated factors and the original indexes using the coefficient of determination in regression analysis. In the third column of Table 1, the three indexes with the highest R-squared of the marginal regressions are shown, with the R-squared in parentheses.

For the United States, we can interpret the first factor as related to jobs and general economic activity, the second related to construction and property, and the third related to manufacturing and investment. For the European countries, we interpret the first factor as a general economic performance. We interpret the second factor of Germany and Italy and the third factor of Spain and France as related to the Eurozone crisis because it involves generally the indexes of *fiscal policy news*, *currency and foreign exchange*, and other indexes related to credit or construction.

Table 1: Selected factors and main components

Country	Factor	Main components
United	f_1^{us} (0.38)	Jobs (0.68), Economy news (0.61), Currency & Foreign Exchange (0.56)
States	f_2^{us} (0.23)	Property (0.71), Construction (0.56), Lending & Credit (0.37)
	f_3^{us} (0.11)	Manufacturing (0.41), Lending & Credit (0.25), Industrial Materials & Equipment (0.21)
Germany	f_1^{de} (0.55)	Construction (0.48), Lending & Credit (0.42), Jobs (0.42)
	f_2^{de} (0.18)	Currency & Foreign Exchange (0.61), Fiscal policy news (0.32), Construction (0.13)
France	f_1^{fr} (0.50)	Construction (0.60), Industrial Materials & Equipment (0.42), Economy news (0.25)
	f_2^{fr} (0.17)	Lending & Credit (0.45), Property (0.37), Currency & Foreign Exchange (0.22)
	f_3^{fr} (0.11)	Currency & Foreign Exchange (0.45), Economy news (0.20), Property (0.08)
Italy	f_1^{it} (0.39)	Lending & Credit (0.27), Jobs (0.13), Property (0.11)
	f_2^{it} (0.16)	Fiscal policy news (0.22), Currency & Foreign Exchange (0.21), Property (0.03)
	f_3^{it} (0.12)	Economy news (0.34), Automobile Industry (0.11), Currency & Foreign Exchange (0.11)
Spain	f_1^{sp} (0.33)	Lending & Credit (0.30), Fiscal policy news (0.30), Currency & Foreign Exchange (0.18)
	f_2^{sp} (0.21)	Property (0.30), Automobile Industry (0.29), Economy news (0.14)
	f_3^{sp} (0.19)	Currency & Foreign Exchange (0.54),Fiscal policy news (0.17), Lending & Credit (0.09)

Note: This table reports the factors extracted with principal component analysis using 10 indexes of economic activity: economic news, jobs, fiscal policy news, credit and lending, manufacturing, industrial materials and equipment, construction and maintenance, property, currency and foreign exchange, and the automobile industry. For each country, the factors with an eigenvalue greater than 1 are selected. In the second column, in parentheses, is the proportion of the overall variance explained by each of the factors. The third column shows the three indexes with the highest R-squared of the marginal regressions, with the respective R-squared in parentheses. The sample consists of 469 observations from 2004w1 to 2012w51. The Kaiser-Meyer-Olkin measure of sampling adequacy is 0.81 for the United States, 0.90 for Germany, 0.87 for France, 0.92 for Italy, and 0.84 for Spain.

We treat the US factors as global and the European country factors as country specific. To make sure that the specific factors do not contain redundant information, we regress them on the three US factors:

$$f_{l,t}^{i} = \alpha_0 + \alpha_1 f_{1,t}^{us} + \alpha_2 f_{2,t}^{us} + \alpha_3 f_{3,t}^{us} + \mu_t, \tag{6}$$

for any factor l of country i. We then use the residuals from each regression as specific factors that are orthogonal to the global factors, defining them as $\hat{f}_{l,t}^{i}$. The estimation results are reported in Appendix C.3. The country-specific factors share a lot of information with the US factors, with an average R-squared of 0.43. The regression coefficients are statistically significant at the 1 percent level in most cases. In the application, the global factors together with the orthogonalized specific factors are used to explain the European stock and bond comovements.

3.3 Google trends based factors and economic activity

Having constructed the factors, we investigate whether they are correlated with macroeconomic fundamentals. We carry out the analysis with three key monthly series: unemployment rate, consumer price index, and industrial production index. We first compute the monthly average of the factors. For each country, we regress each of the economic variables on the corresponding factors. To make the variables stationary, we include unemployment rate in first differences and consumer price index and industrial production index in growth rates. Table 2 shows the results.

For all countries, the estimated factors have a statistically significant correlation with at least one economic variable. In all cases, the factors are negatively correlated with economic activity, either in the form of higher changes in unemployment, lower industrial production growth or lower inflation rate. The estimated factors are identified up to a sign change, but this association with economic activity, will allow an economic interpretation of the sign

Table 2: Google factors and monthly economic activity

Variable	f_1^i		f_2^i		f_3^i		R^2	Obs
United States								
Unemployment rate	0.041	(4.44)**	0.023	(2.12)*	0.059	(4.05)**	0.37	107
Consumer Price Index	-0.001	(-2.10)*	-0.000	(-0.90)	-0.000	(-0.47)	0.07	107
Industrial Production	-0.002	(-3.93)**	-0.000	(-0.21)	-0.002	(-3.17)**	0.26	107
Germany								
Unemployment rate	0.021	(4.94)**	0.028	(4.28)**			0.30	107
Consumer Price Index	-0.072	(-3.91)**	-0.018	(-0.64)			0.13	107
Industrial Production	-0.118	(-1.40)	-0.394	(-2.99)**			0.10	107
France								
Unemployment rate	0.008	(1.36)	0.025	(2.62)**	0.024	(2.08)*	0.12	107
Consumer Price Index	-0.032	(-2.04)*	0.042	(1.53)	-0.046	(-1.37)	0.07	107
Industrial Production	-0.015	(-0.02)	-0.097	(-0.67)	-0.351	(-1.99)*	0.04	107
Italy								
Unemployment rate	0.017	(1.21)	0.009	(0.47)	0.023	(1.02)	0.03	107
Consumer Price Index	-0.063	(-1.30)	-0.057	(-0.84)	0.061	(0.72)	0.03	107
Industrial Production	-0.277	(-2.59)*	-0.373	(-2.48)*	-0.171	(-0.92)	0.13	107
Spain								
Unemployment rate	0.068	(5.07)**	0.016	(1.15)	0.103	(6.97)**	0.46	107
Consumer Price Index	-0.099	(-1.91)	-0.035	(-0.68)	-0.011	(-0.19)	0.04	107
Industrial Production	-0.337	(-2.53)*	-0.071	(-0.53)	-0.240	(-1.75)	0.10	107

Note: This table reports the estimation results of the regression of each economic indicator on all the extracted factors of the respective country. The weekly factors are averaged for the month. Unemployment rate is in first differences, while consumer price index and industrial production index are in growth rates. The sample consists of 107 observations from 2004m1 to 2012m11. In parentheses is the t-statistic of the coefficient.** means significant at 1 percent and * means significant at 5 percent.

of the coefficients in the regressions in the following section. We repeat the exercise with the orthogonalized factors. The sign of the relationship is the same for all factors with the exception of the third factor of France (Appendix C.4).

We carry out a further robustness exercise for the United States. We retrieve 25 weekly and monthly economic series from the St. Louis FED Federal Reserve Economic Data, divided in the following categories: labor market, industrial production, housing market, trade, prices, and income. For most of the considered variables, we do not reject the null of unit root, so we make the variables stationary by taking the first differences. The description of the variables and the correlation with the factors are presented in Appendix C.4. The sign of the regression coefficient confirms that the US factors are negatively related to economic activity. The test statistics indicate that most of the economic fundamentals under consideration are related with the first and third factors but less so with the second factor. The R-squared is 0.2 on average for the 25 series.

4 Empirical results

4.1 Predicting cross-country stock and bond comovement

We run the following regression:

$$Cov_{t+1}\left(r_{i,t+1}^{k}, r_{j,t+1}^{k}\right) = \nu + \phi' \mathbf{f}_t^{us} + \lambda' \hat{\mathbf{f}}_t^{i} + \pi' \hat{\mathbf{f}}_t^{j} + \varepsilon_{t+1}, \tag{7}$$

where $Cov_{t+1}\left(r_{i,t+1}^{k}, r_{j,t+1}^{k}\right)$ is the covariance between asset returns in countries i and j, for k =stock return, bond return; $\mathbf{f}_t^{us}$ is the vector of global factors; and $\hat{\mathbf{f}}_t^{i}$ and $\hat{\mathbf{f}}_t^{j}$ are the vectors of specific factors of countries i and j, respectively. The estimation results are presented in Tables 3 and 4. Robust standard errors are used.

Table 3 shows that the global factors are the main determinants of international stock comovements; they are statistically significant at the 1 percent level for all country pairs. All global factors have a positive impact on the covariance between European stock returns.

Table 3: Cross-country stock market returns covariance

	$DE-FR$	$DE-IT$	$DE-SP$	$FR-IT$	$FR-SP$	$IT-SP$
			Global			
f_1^{us}	0.341 (8.98)**	0.349 (8.85)**	0.353 (7.76)**	0.315 (9.48)**	0.329 (8.29)**	0.308 (8.99)**
f_2^{us}	0.281 (7.21)**	0.325 (8.29)**	0.306 (6.95)**	0.302 (9.38)**	0.320 (8.03)**	0.337 (10.68)**
f_3^{us}	0.365 (7.08)**	0.369 (6.86)**	0.371 (6.37)**	0.311 (6.79)**	0.339 (6.26)**	0.292 (6.26)**
			Country-specific			
$\hat{f}_1^{de}$	0.095 (2.50)*	0.035 (0.97)	0.088 (2.12)*			
$\hat{f}_2^{de}$	0.249 (3.29)**	0.298 (3.62)**	0.171 (1.94)			
$\hat{f}_1^{fr}$	-0.084 (-2.37)*			-0.077 (-2.99)**	-0.031 (-0.89)	
$\hat{f}_2^{fr}$	0.021 (0.49)			0.053 (1.34)	0.038 (0.82)	
$\hat{f}_3^{fr}$	-0.130 (-2.37)*			-0.013 (-0.24)	-0.034 (-0.57)	
$\hat{f}_1^{it}$		0.022 (0.46)		0.048 (1.25)		0.044 (1.01)
$\hat{f}_2^{it}$		-0.012 (-0.25)		0.039 (0.83)		0.008 (-0.14)
$\hat{f}_3^{it}$		-0.031 (-0.80)		0.019 (0.52)		0.019 (0.53)
$\hat{f}_1^{sp}$			0.019 (0.44)		0.037 (0.88)	-0.040 (-0.96)
$\hat{f}_2^{sp}$			0.081 (1.87)		0.050 (0.96)	0.069 (1.70)
$\hat{f}_3^{sp}$			0.160 (1.82)		0.144 (2.04)*	0.161 (2.24)*
R^2	0.602 [0.571]	0.598 [0.572]	0.572 [0.547]	0.596 [0.585]	0.565 [0.550]	0.573 [0.556]
Obs	408	408	408	408	408	408

Note: This table reports the estimation results of the regression of the covariance of stock market returns in two countries on the global and orthogonalized country-specific factors [see Equation (7)]. The coefficients reported were multiplied by 10^3 for readability. The sample consists of 408 observations from 2004w1 to 2011w45. In parentheses is the t-statistic of the coefficient using robust standard errors. ** means significant at 1 percent and * means significant at 5 percent. In brackets is the R-squared of the regression with only global factors.

Given the relationship of the factors with economic activity [see Table 2], all the different dimensions of a US recession increase the covariance in European stock markets. The R-squared of each regression is between 0.57 and 0.60 and remains high if we exclude the specific factors (between 0.55 and 0.57). Still, some are statistically significant. A worsening of economic activity in Germany increases the covariance between the stock market returns of all other European countries. The third factor from Spain also has a positive effect on the covariance. As for France, there are mixed effects, and for Italy, none of the specific factors are significant.

For the bond market, the results are somewhat different [see Table 4]. First, all factors explain less variation than for the stock market. The R-squared varies only between 0.23 and 0.35. Also, the specific factors are relatively more important. When we exclude them, the R-squared falls from an average of 0.28 to 0.19. This is particularly visible in the covariances with Italian and Spanish bond returns.

Similarly to the stock market returns, the US global factors have a statistically significant impact on the covariances between European bond returns. The first and third global factors positively affect the covariances. The second factor has more mixed effects, with a positive

Table 4: Cross-country bond market returns covariance

	DE-FR	**DE-IT**	**DE-SP**	**FR-IT**	**FR-SP**	**IT-SP**
			Global			
f_2^{us}	0.120 (6.83)**	0.083 (5.89)**	0.140 (7.43)**	0.008 (1.17)	0.076 (7.42)**	0.034 (2.01)*
f_2^{us}	0.186 (9.93)**	-0.012 (-0.55)	0.044 (1.64)	-0.069 (-7.82)**	0.046 (3.29)**	0.113 (4.49)**
f_3^{us}	0.116 (4.47)**	0.094 (3.40)**	0.164 (4.82)**	0.030 (2.75)**	0.083 (4.08)**	0.036 (0.90)
			Country-specific			
$\hat{f}_1^{de}$	0.050 (1.84)	0.013 (0.55)	-0.054 (-1.99)*			
$\hat{f}_2^{de}$	0.090 (2.11)*	-0.051 (-1.15)	-0.171 (-2.82)**			
$\hat{f}_1^{fr}$	-0.010 (-0.74)			0.0378 (3.71)**	0.057 (2.23)*	
$\hat{f}_2^{fr}$	0.032 (1.01)			0.322 (2.02)*	0.071 (1.60)	
$\hat{f}_3^{fr}$	-0.083 (-2.26)*			-0.066 (-3.48)**	-0.141 (-2.77)**	
$\hat{f}_1^{it}$		-0.014 (-0.43)		0.007 (0.67)		0.127 (1.27)
$\hat{f}_2^{it}$		-0.170 (-4.27)**		-0.047 (-2.49)*		-0.044 (-0.52)
$\hat{f}_3^{it}$		-0.140 (-3.18)**		-0.057 (-4.00)**		0.346 (2.95)**
$\hat{f}_1^{sp}$			0.101 (2.01)*		0.014 (0.55)	-0.100 (-2.44)*
$\hat{f}_2^{sp}$			-0.073 (-3.53)**		0.013 (0.30)	0.060 (0.80)
$\hat{f}_3^{sp}$			0.612 (1.31)		0.013 (0.30)	0.013 (0.13)
R^2	0.356 [0.336]	0.253 [0.127]	0.282 [0.239]	0.279 [0.215]	0.270 [0.194]	0.236 [0.049]
Obs	408	408	408	408	408	408

Note: This table reports the estimation results of the regression of the covariance of bond market returns in two countries on the global and orthogonalized country-specific factors [see Equation (7)]. The coefficients reported were multiplied by 10^3 for readability. The sample consists of 408 observations from 2004w1 to 2011w45. In parentheses is the t-statistic of the coefficient using robust standard errors. ** means significant at 1 percent and * means significant at 5 percent. In brackets is the R-squared of the regression with only global factors.

sign in four cases and a negative, statistically significant effect in only one case. Overall, if we combine the signs of the coefficients of the impact of Google search-based factors on key economic variables [see Table 2] with those of the impact of the factors on the cross-country bond returns covariance [see Table 4], we conclude that a worsening of the US economic activity raises the covariance between European sovereign bond returns.

The specific factors contribute to the comovements in the European bond markets. However, the sign of their effects changes depending on the pairs of countries. A deterioration of economic activity in Germany raises the covariance with France but lowers it with Spain. For Italy, worsening activity lowers the covariance with France but raises it with Spain. Also, the Spanish first factor raises the covariance with Germany but lowers it with Italy.

4.2 Predicting within-country stock and bond comovement

4.2.1 Predicting covariances

We look at the comovement between stock and bond returns within a country. In particular, we estimate the following regression:

$$Cov_{t+1}\left(r^s_{i,t+1}, r^b_{i,t+1}\right) = \nu + \phi'\mathbf{f}^{us}_t + \lambda'\hat{\mathbf{f}}^i_t + \varepsilon_{t+1}, \tag{8}$$

where $Cov_{t+1}\left(r^s_{i,t+1}, r^b_{i,t+1}\right)$ is the covariance between stock and bond returns in country i and f^{us}_t and $\hat{f}^i_t$ are the vectors of global factors and specific factors of country i, respectively. The results using parametric measures of covariance are provided in Table 5.

Table 5 shows that the covariances between stock and bond returns of the same European country are again driven by the global factors. All global factors have negative and statistically significant effects, with the exception of the second global factor has a positive sign in the case of Germany and France. Thus, generally if we combine the signs of the coefficients with those in Table 5, as opposed to the results obtained for cross-country comovement, it seems that all the different dimensions of a US recession decrease the covariance between stock and bond markets of same European country. The country-specific factors only seem relevant for the comovements between stock and bond returns in Italy, as the R-squared drops from 0.23 to 0.08 when we exclude them.

Table 5: Stock and Bond market returns covariance (using DCC model)

	Germany	*France*	*Italy*	*Spain*
		Global		
f^{us}_1	-0.058 (-6.37)**	-0.051 (-11.32)**	-0.011 (-1.72)	-0.018 (-2.45)*
f^{us}_2	-0.113 (-9.42)**	-0.055 (-9.42)**	0.038 (4.37)**	0.020 (2.24)*
f^{us}_3	-0.051 (-3.38)**	-0.051 (-6.85)**	-0.031 (-2.86)**	-0.040 (-3.51)**
		Country		
$\hat{f}^{de}_1$	-0.014 (-1.27)			
$\hat{f}^{de}_2$	-0.082 (-3.37)**			
$\hat{f}^{fr}_1$		0.006 (1.25)		
$\hat{f}^{fr}_2$		-0.018 (-2.00)*		
$\hat{f}^{fr}_3$		0.003 (0.29)		
$\hat{f}^{it}_1$			0.001 (0.10)	
$\hat{f}^{it}_2$			0.063 (3.75)**	
$\hat{f}^{it}_3$			0.092 (8.01)**	
$\hat{f}^{sp}_1$				-0.020 (-1.92)*
$\hat{f}^{sp}_2$				0.001 (0.11)
$\hat{f}^{sp}_3$				0.028 (1.55)
R^2	0.297 [0.276]	0.440 [0.432]	0.233 [0.081]	0.094 [0.073]
Obs.	408	408	408	408

Note: This table reports the estimation results of the regression of the DCC covariance between bond and stock market returns in the same country on the global and country-specific factors, see Equation (8). The coefficients reported were multiplied by 10^3 for readability. Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression with only global factors.

4.2.2 Predicting variances

Although the main focus of this paper is on explaining the time series of international market comovements measured by the covariances between international asset returns, in this subsection we consider implications for the second moments of the asset returns and investigate the main determinants of their volatilities. In particular, we consider the following regression:

$$Var_{t+1}\left(r_{i,t+1}^{k}\right) = \nu + \phi'\mathbf{f}_t^{us} + \lambda'\hat{\mathbf{f}}_t^{i} + \epsilon_{t+1}, \tag{9}$$

where $Var_{t+1}\left(r_{i,t+1}^{k}\right)$ is the variance of the return in country i, for k =stock return, bond return; f_t^{us} is the vector of global factors; and $\hat{f}_t^i$ is the vector of specific factors of country i, respectively. The estimation results are presented in Tables 6 and 7. Robust standard errors are used.

Table 6 summarizes the results of the impact of global and country specific factors on the volatilities of European stock returns. From this and as for the covariances in the previous section, we see that the global factors are the main determinants of European stock comovements. Their effects are positive for all countries under consideration and they are statistically significant at the 1 percent level. implying that the different dimensions of a US recession increase the volatility in European stock markets. The R-squared of each regression is between 0.54 and 0.57 and remains high if we exclude the specific factors (between 0.52 and 0.57). The sign and statistical significance of the impact of country-specific factors is unstable and changes depending on the countries, except for Germany.

For the bond market, the results are somewhat different [see Table 7]. Although the sign of the impact of global factors remains positive, its statistical significance is less important compared to the results obtained for stock market, in particular for Italy and Spain. Moreover, the sign and statistical significance of the impact of country-specific factors is unstable and changes depending on the country, except for Germany. Overall, all factors explain less variation than for the stock market. The R-squared varies only between 0.11 and 0.26, or between 0.05 and 0.24 when we exclude the specific factors. The latter numbers indicate that the specific factors are relatively more important for explaining the bond market volatility.

Table 6: Stock market returns variance (using 1st stage DCC model)

	Germany	*France*	*Italy*	*Spain*
		Global		
f_2^{us}	0.410 (7.52)**	0.329 (8.68)**	0.354 (9.85)**	0.330 (8.16)**
f_2^{us}	0.325 (5.99)**	0.287 (7.48)**	0.369 (11.41)**	0.364 (9.32)**
f_3^{us}	0.454 (6.30)**	0.349 (6.74)**	0.337 (6.55)**	0.316 (5.79)**
		Country		
$\hat{f}_1^{de}$	0.078 (1.96)			
$\hat{f}_2^{de}$	0.260 (2.63)**			
$\hat{f}_1^{fr}$		-0.050 (-2.19)*		
$\hat{f}_2^{fr}$		0.042 (1.12)		
$\hat{f}_3^{fr}$		-0.024 (-0.45)		
$\hat{f}_1^{it}$			-0.022 (-0.51)	
$\hat{f}_2^{it}$			0.068 (1.25)	
$\hat{f}_3^{it}$			-0.008 (-0.19)	
$\hat{f}_1^{sp}$				-0.008 (-0.18)
$\hat{f}_2^{sp}$				0.076 (1.88)
$\hat{f}_3^{sp}$				0.149 (2.11)*
R^2	0.539 [0.520]	0.571 [0.566]	0.566 [0.564]	0.551 [0.537]
Obs.	408	408	408	408

Note: This table reports the estimation results of the regression of the variance of stock market returns in a given country (Germany, France, Italy, Spain) on the global and orthogonalized country-specific factors [see Equation (9)]. The coefficients reported were multiplied by 10^3 for readability. The sample consists of 408 observations from 2004w1 to 2011w45. In parentheses is the t-statistic of the coefficient using robust standard errors. ** means significant at 1 percent and * means significant at 5 percent. In brackets is the R-squared of the regression with only global factors.

Table 7: Bond market returns variance (using 1st stage DCC model)

	Germany	*France*	*Italy*	*Spain*
		Global		
f_2^{us}	0.169 (5.01)**	0.073 (5.96)**	0.030 (1.77)	0.046 (1.76)
f_2^{us}	0.370 (9.27)**	0.097 (7.12)**	0.101 (4.46)**	0.239 (6.18)**
f_3^{us}	0.201 (3.62)**	0.089 (4.85)**	0.040 (0.99)	0.051 (0.89)
		Country		
$\hat{f}_1^{de}$	0.088 (1.97)*			
$\hat{f}_2^{de}$	0.214 (2.49)*			
$\hat{f}_1^{fr}$		0.036 (2.11)*		
$\hat{f}_2^{fr}$		0.065 (2.92)**		
$\hat{f}_3^{fr}$		-0.057 (-1.80)		
$\hat{f}_1^{it}$			0.065 (0.89)	
$\hat{f}_2^{it}$			0.009 (0.20)	
$\hat{f}_3^{it}$			0.310 (3.33)**	
$\hat{f}_1^{sp}$				-0.089 (-1.08)
$\hat{f}_2^{sp}$				-0.113 (-2.11)*
$\hat{f}_3^{sp}$				-0.095 (-1.06)
R^2	0.262 [0.243]	0.245 [0.216]	0.227 [0.051]	0.115 [0.097]
Obs.	408	408	408	408

Note: This table reports the estimation results of the regression of the variance of bond market returns in a given country (Germany, France, Italy, Spain) on the global and orthogonalized country-specific factors [see Equation (9)]. The coefficients reported were multiplied by 10^3 for readability. The sample consists of 408 observations from 2004w1 to 2011w45. In parentheses is the t-statistic of the coefficient using robust standard errors. ** means significant at 1 percent and * means significant at 5 percent. In brackets is the R-squared of the regression with only global factors.

5 Robustness and additional results

5.1 Nonparametric covariances

We use as a robustness check a nonparametric measure of covariance, given in Equation (4), with $m = 20$ weeks rolling window. The results are shown in Appendix D.1. The R-squared remains similar to that in the benchmark regressions in the previous section: around 0.60 for the stock market and 0.25 for the sovereign bond market. The coefficients of the global factor are statistically significant in both markets, with the three global factor always positive, confirming that the worsening of economic activity in the United States raises the covariance between asset returns in Europe.

Concerning the comovement between stock and bond returns within the same European country, Appendix D.4 shows that the results obtained in Section 4.2.1 are quite robust when we use the nonparametric measure of covariance instead of parametric one, albeit weaker for Italy and Spain.

5.2 Predicting correlations

As an alternative measure of comovement, common in the literature, we use the correlation coefficient. We run the following regressions:

$$Correl_{t+1}\left(r_{i,t+1}^{k}, r_{j,t+1}^{k}\right) = \nu + \phi' \mathbf{f}_t^{us} + \lambda' \hat{\mathbf{f}}_t^{i} + \pi' \hat{\mathbf{f}}_t^{j} + u_{t+1}, \tag{10}$$

where $Correl_{t+1}\left(r_{i,t+1}^{k}, r_{j,t+1}^{k}\right)$ is the correlation between the asset returns in country i and in country j. The estimation results for both the parametric (DCC) and nonparametric (Equation (5)) correlations' measures are presented in Appendices D.2 and D.3, respectively.

For the stock market correlation, the coefficients of the global factors have the same positive sign as that of the covariance. A recession in the United States raises the correlation between European stocks. The specific factors have heterogeneous effects per country pair. The R-squared varies between 0.10 and 0.36. The results are robust to the use of the nonparametric measure of correlation in Equation (5).

For the bonds market correlation, the third factor have a positive and statistically significant coefficient while the second factor has a negative coefficient. While a worsening of economic condition in the United States is more associated with manufacturing and investment raises the correlation in Europe, a worsening of conditions associated with lending, construction, and property lowers the correlation. The first global factor also has a positive effect but is generally statistically insignificant. Furthermore, we find that specific factors contribute to explaining the correlations between bond market returns, and the sign of their effect changes depending on the countries under consideration. These results are confirmed globally when we use the nonparametric approach. The R-squared for bond markets varies between 0.16 and 0.28.

Regarding the comovement between stock and bond returns within the same European country, we re-estimated Equation (8) after replacing the covariance by the correlation measure. The results using both parametric and non-parametric correlations' measures are reported in Appendix D.4. The results using correlation measure are somehow different from those we obtained using covariance measure (see Section 4.2.1). However, when we only focus on the statistically significant coefficients, we find that the results using covariance and correlation are quite similar, thus the economic interpretation of the effects remained the same as in Section 4.2.1.

5.3 Impact of European factors

Here we examine the impact of regional (European) factors on cross-country stock and bond comovements. European factors were estimated in a similar way as country-specific factors, but using joint information on European countries for the same period of time. We use the series for all European countries and extract three factors. We consider the following regression where the country-specific factors in Equation (8) where replaced by the European factors:

$$Cov_{t+1}\left(r^k_{i,t+1}, r^k_{j,t+1}\right) = \nu + \phi' \mathbf{f}^{us}_t + \lambda' \hat{\mathbf{f}}^{eu}_t + \varepsilon_{t+1}, \tag{11}$$

where $Cov_{t+1}\left(r_{i,t+1}^{k}, r_{j,t+1}^{k}\right)$ is the covariance between asset returns in countries i and j, for k =stock return, bond return; f_t^{us} is the vector of global factors; and $\hat{f}_t^{eu}$ is the vector of regional factors. We did not include country-specific factors into the regression in (11) to avoid multicollinearity problems since the regional factors were constructed using information from specific countries. The results are provided in Appendix D.5.

Global factors are the dominant factors for the European stock and bond comovements, respectively. The new regional factors do not add much to the predictive content of global factors for predicting the covariances between European stock and bond returns. The sign of the impact of global factors on both stock and bond market comovements is still positive in general, thus the economic interpretation of this impact is still the same as in Section 4.1. Regarding the regional factors, only the third factor affects the European stock and bond comovements, and it has a positive effect on stock comovements and negative one (except for the pair Italy-Spain) on bond comovements.

5.4 Impact of observed and latent macro factors

In this subsection we provide additional results that show the impact of macroeconomic based risk factors on the cross-country stock market and bond market covariances and compare them with those based on *Google* data. The data used for this exercise is a monthly data, because most of the macro variables are observed at least at monthly frequency. We extract three macro based risk factors from 20 US macroeconomic series that were previously used in Section 3.3, using principle componant analysis. As an alternative, we also looked at the impact of observed macro variables (unemployment rate, consumer price index and industrial production). The results are reported in Appendix D.6.

The U.S. macro based risk factors provide significant information for the cross-country stock market covariance. Their impact is statistically significant at 1% significance level. The R-squared is quite high and varies between 0.56 and 0.69, although it is lower than the factors extracted from *Google* data. Notice that several of the *Google* factors are now not significant, because of the reduction of the number of observations. If we consider the macro variables directly, they have a statistically significant effect on the comovement among

European stock markets. However, the sign of this effect varies: unemployment rate and industrial production have a negative impact, whereas consumer price index has a positive impact on the stock market covariance. The R-squared varies between 0.36 and 0.45, which indicates that these variables are informative about the comovement but less than both the *Google* and macro based risk factors.

The macro factors also have an effect on the bond market covariance, but it is economically (magnitude of the coefficients) and statistically less significant compared to the one obtained for stock market covariance, which is consistent with the results with *Google* data. The decreases in economic significance is confirmed by a lower R-squared that varies between 0.19 and 0.50. The signs of the coefficients are quite similar to those obtained for stock market covariance, except for the pairs Germany-Italy and Germany-Spain.

6 Implications for international risk diversification

We now turn to the implications of our previous results for international risk diversification. We construct international asset portfolios using *Google* search-based factors and evaluate their performance. We use a novel approach that consists of modeling portfolio weights directly. Portfolio weights modeling was proposed by Brandt and Santa-Clara (2009) to overcome the classical problems of the mean-variance portfolio. Brandt *et al.* (2009) model portfolio weights as a function of predetermined economic variables. They consider that all assets in a given portfolio are related to common variables through different functions (coefficients). Their methodology is computationally simple, produces sensible weights, and performs better. Bouaddi and Taamouti (2013) extend this approach to model the weights as a function of *latent factors* that summarize the information in a large number of economic variables representing different sectors of the economy using a factor model with principal components analysis as in Stock and Watson (2002a, 2002b) and Bai and Ng (2002). In our setting, we assume that the weights are functions of the global factors.

Consider a portfolio constructed using stocks or bonds separately from n countries, with the vector of weights at time t given by $\omega_t = (\omega_{1,t}, ..., \omega_{n,t})^\top$, with $\sum_j \omega_{j,t} = 1$. We modify the weight function in Bouaddi and Taamouti (2013) and assume it is a linear function of the *global factors*. Thus, we solve the conditional portfolio choice problem by parameterizing portfolio weights as follows:

$$\omega_{j,t} = \vartheta_{j,0} + \vartheta'_{j,1} f^{us}_{1,t} + \vartheta'_{j,2} f^{us}_{2,t} + \vartheta'_{j,3} f^{us}_{3,t}, \quad j = DE, FR, SP, \tag{12}$$

where $\vartheta_{j,1}$, $\vartheta_{j,2}$ and $\vartheta_{j,3}$ are the parameters measuring the response of the weight in country j to the corresponding *global factor*. The matrix $\boldsymbol{\vartheta}$ of the above coefficients is chosen optimally by maximizing the investor's average utility

$$\hat{\boldsymbol{\vartheta}} = Arg\max_{\boldsymbol{\vartheta}} \left\{ \frac{1}{T} \sum_{t=1}^{T-1} u\left(\omega_t^{\top} r_{t+1}\right) \right\}, \tag{13}$$

for a given utility function $u(.)$, where r_{t+1} is the vector of returns of the n assets (stocks or bonds). While the specification of $u(.)$ is a matter of choice, the power-utility function of the form

$$u(\omega_t^{\top} r_{t+1}) = \frac{(1 + \omega_t^{\top} r_{t+1})^{1-\zeta}}{1-\zeta}$$

gives great flexibility in the empirical analysis as it takes into account not only the mean and variance, but also higher-order moments such as skewness and kurtosis, without introducing additional parameters. The portfolios selected under the constant relative risk aversion utility function maximize the mean and skewness and minimize the variance of portfolio returns [see Brandt *et al.* (2009, page 3417)]. Following the literature, we take the risk aversion, ζ, as equal to 5 and 8. To evaluate the performance of our portfolios, we use a leading performance measure, i.e., the Sharpe ratio, given by

$$SR\left(\omega_t\right) = \frac{\mu\left(\omega_t\right)}{\sigma\left(\omega_t\right)},$$

where $\mu_p\left(\omega\right)$ and $\sigma_p\left(\omega\right)$ are the mean and standard deviation of portfolio returns, respectively. Higher values of the Sharpe ratio indicate good performance. However, if portfolio return distributions are skewed, then a favorable shift in probability mass may result in a lower Sharpe ratio. Since the latter quantifies and reward risk through two-sided type measures, positive and negative deviations from the benchmark are weighted in the same manner. Farinelli and Tibiletti (2008) propose one sided measures of performance [hereafter FT ratios] that capture two types of asymmetrical information: (1) "good" volatility (above the benchmark) and "bad" volatility (below the benchmark), and (2) asymmetrical preference to bet on potential high stakes and the aversion against possible huge losses. Thus, we evaluate the performance of previous portfolios using also the following FT ratios:

$$FT\left(\omega_t\right) = \frac{\left(E\left[\left|r_{p,t}\left(\omega_t\right) - b\right| \mid r_{p,t}\left(\omega_t\right) > b\right]^p\right)^{\frac{1}{p}}}{\left(E\left[\left|r_{p,t}\left(\omega_t\right) - b\right| \mid r_{p,t}\left(\omega_t\right) < b\right]^q\right)^{\frac{1}{q}}}, \tag{14}$$

where $r_{p,t}(\omega)$ denotes the portfolio returns, b is a benchmark threshold, and p and q are positive constants. In our empirical analysis we take b equal to zero, but other values can be considered. The FT ratios can be viewed as general risk-reward indices suitable to compare skewed returns with respect to a benchmark. For some particular values of p and q, the FT ratios correspond to some known indices. For $p = q = 1$, we have the Omega index proposed by Cascon et al. (2003) and for $p = 1$ and $q = 2$ we get the Upside Potential index suggested by Sortino et al. (1999). The analysis covers the four European countries described in Section 3 and is done separately for stocks and bonds.

We build two portfolios based on *Google* search data. The first portfolio is constructed as a function of the global factors of the previous week by allowing weekly adjustments. In the second portfolio, we average the information over the month and only allow monthly adjustments, as a function of information of the previous month. We distinguish these two portfolios to understand whether the gains come from the information itself or from its frequency. We compare the portfolios to an equally weighted portfolio and one with constant weights, estimated from Equation (12) with only the constant terms. We do an in-sample and an out-of-sample exercise. In the in-sample exercise, the portfolio weights are estimated using the whole sample. The out-of-sample exercise is for the last year of the sample (52 weeks or 12 months). We estimate the model up to a given week (month) and use the estimates to determine the portfolio weights in the following week (month). The average monthly portfolio returns, their standard deviations, and the Sharpe and FT (for $p = q = 1$) ratios are presented in Table 8. Additional portfolio performance results that correspond to different values of parameters p and q in the FT ratio formula in (14) are reported in Appendix E.3.

The portfolio based on *Google* search factors generally outperforms the others, having higher returns and Sharpe and FT ratios, especially for a stock market with a low risk aversion coefficient. It is not surprising given that the global factors explained the covariance in the stock market more than they did the covariance in the bond market. Although there are gains from having the monthly portfolio, the weekly portfolio generally performs better. The equally weighted and constant-weights portfolios, especially in the out-of-sample exercise, both have a negative return, and so does the portfolio constructed at a monthly frequency. The weekly portfolio constructed using the global factors has high and positive returns, particularly on the stock market. As the crisis unfolded quickly, having a portfolio with weekly adjustments based on consistent data proves a crucial element for good performance.

Appendix E.1 reports the estimated coefficients of the weights of the weekly portfolio. The three global factors have significant effects on the weights of stocks and bonds of most countries. However, the sign pattern is less apparent and depends on the countries. Appendix E.2 displays the estimated weights of the factor-based portfolio for the two markets and the four countries. The portfolio weights are time-varying and more volatile after the Eurozone crisis of 2008. Overall, the optimal portfolio that uses *Google* search factors does not reflect any unreasonably extreme bets.

To provide an economic interpretation of the factor-based portfolio weights, Appendix E.2 reports the results of marginal regressions of the country weights for the two markets on three US macroeconomic variables: unemployment rate in first differences, and consumer price index and industrial production index in growth rates. The three macroeconomic variables have, in general, statistically significant effects on the weights, particularly the industrial production index. For the weekly portfolio, lower industrial production raises the weight on German and Italian bonds and stocks, relative to the French and Spanish ones.

Table 8: Portfolio comparison

	Stock Market				Bond Market			
Portfolio	Mean	St. Dev.	SR	FT	Mean	St. Dev.	SR	FT
In-sample								
Equally weighted	0.0%	0.055	0.000	0.755	0.0%	0.050	0.009	0.904
Risk Aversion=5								
Constant weights	1.6%	0.060	0.268	1.053	1.1%	0.070	0.152	1.313
Google (weekly)	5.3%	0.121	0.435	1.455	4.6%	0.169	0.275	2.528
Google (monthly)	4.2%	0.101	0.418	1.568	2.7%	0.109	0.246	1.611
Risk Aversion=8								
Constant weights	0.9%	0.053	0.170	1.139	0.6%	0.057	0.107	1.058
Google (weekly)	3.4%	0.088	0.393	1.189	2.9%	0.110	0.266	2.056
Google (monthly)	2.5%	0.070	0.362	1.414	1.6%	0.075	0.213	1.596
Out-of-sample (1 year)								
Equally weighted	-1.9%	0.068	-0.283	0.048	-0.6%	0.067	-0.108	0.642
Risk Aversion=5								
Constant weights	-0.1%	0.072	-0.008	0.489	-2.0%	0.087	-0.228	0.732
Google (weekly)	11.8%	0.264	0.447	1.215	1.7%	0.547	0.031	0.551
Google (monthly)	-3.2%	0.197	-0.164	0.621	-2.9%	0.393	-0.074	0.303
Risk Aversion=8								
Constant weights	-0.6%	0.070	-0.080	0.394	-2.1%	0.077	-0.279	0.926
Google (weekly)	7.1%	0.198	0.360	2.099	0.2%	0.328	0.005	0.508
Google (monthly)	-3.1%	0.133	-0.231	0.933	2.9%	0.127	0.230	1.399

Note: The table summarizes the portfolio performance at a monthly frequency. The portfolios are constructed based on the weight function in (12) and the coefficients in Equation (13), estimated using the generalized method of moments. The instruments used consist of four lags of $r_{j,t+1}$, $r_{j,t+1}f^{us}_{1,t,}$, $r_{j,t+1}f^{us}_{2,t}$, and $r_{j,t+1}f^{us}_{3,t}$. The constant weights portfolios only estimate the constant term $\vartheta_{j,0}$. Two portfolios are constructed using Google search data at weekly and monthly frequencies (reported statistics are for monthly portfolio results). For the weekly estimation, the sample has 402 observations. For the monthly portfolio, the sample has 93 observations from 2004m2 to 2011m10. For the out-of sample portfolio, we show the summary of the portfolio for the last year of the sample (52 weeks or 12 months). We estimate Equation (12) up to week (month) t and compute the weights for the following week (month). SR stands for Sharpe Ratio and FT stands for the Farinelli and Tibiletti (2008) ratio defined in (14) for p=q=1.

It is not surprising that the portfolios in which the weights depend on Google search factors maximize mean return and reduce investment uncertainty (variance). As we found before in Section 3.3, these factors are indicators of relevant economic activities such as unemployment, prices, and output. Flannery and Protopapadakis (2002) examined the impact of 17 macroeconomic variables on the mean and volatility of stock returns and found that most of the above variables affect the mean and/or variance of stock returns [see also Rangvid (2006) and Benzoni *et al.* (2007) among others]. The inflation tends to cause stock prices to go down because the effective rate of return from current dividends and earnings must increase for investors to be interested. Furthermore, Katzur and Spierdijk (2013) show that the relationship between stock returns and inflation has substantial influence on optimal asset allocation. Finally, Ludvigson and Ng (2009) among others found that macroeconomic fundamentals such as output and unemployment have important forecasting power for future conditional mean of bond returns.

7 Conclusion

We characterize stock and bond comovements in a broad class of affine general equilibrium models. In particular, we show that the covariances between stock and bond markets are linear functions of risk factors, which implies that if measures of covariances and risk factors are available, simple econometric techniques can be used to predict stock and bond comovements.

A novel approach is used to measure risk factors based on *Google search*, which can produce economic activity data at a high frequency. The empirical analysis focuses on the Euro Area, before and after the Eurozone crisis. It uses weekly data and the DCC model to measure the covariances in the Euro Area and uses nonparametric measures of covariances to check the robustness. The results indicate that Google search-based factors contain useful information and are able to predict international stock and bond comovements.

We find that most of the variation in the covariance between European stock market returns is driven by global factors, and more concretely, by US economic conditions. Any dimension of a recession in the United States raises the covariance between European stocks. The sovereign bond market is less driven by global factors, with country-specific factors playing a larger role.

We also find that there are substantial gains for investors of using these type of data. Portfolios with time-varying weights as a function of the global factors outperform the equally weighted portfolios and other constantly weighted portfolios, particularly out-of-sample.

A more general conclusion of the study is that the data provided by *Google* search has a huge potential for use in finance. While we restrict ourselves to only 10 indexes, *Google Trends* supplies hundreds of indexes regarding several sectors of economic activity. The data readily available at a weekly frequency for different countries offers great prospects for economists studying the connection between the real economy and finance, as well as for investors focusing on firm, sector, or country finance.

References

[1] d'Addona, S. and A.H. Kind. (2006). International stock-bond correlations in a simple affine asset pricing model. *Journal of Banking & Finance*, 30, 2747-2765

[2] Ammer, J. and J. Mei. (1996). Measuring international economic linkages with stock market data. *The Journal of Finance,* 51, 1743-1763.

[3] d'Amuri, F. (2009). Predicting unemployment in short samples with internet job search query data. *MPRA Paper* 18403.

[4] d'Amuri, F. and J. Marcucci. (2010). "Google it!"Forecasting the US Unemployment Rate with a Google Job Search index. *Fondazione Eni Enrico Mattei Working Papers* 2010.31.

[5] Ang, A. and G. Bekaert. (2002). International asset allocation with regime shifts. *Review of Financial studies*, 15(4), 1137-1187.

[6] Askitas, N. and K. Zimmermann. (2009). Google Econometrics and Unemployment Forecasting. *Applied Economics Quarterly*, 55(2), 107-120.

[7] Bai, J. and S. Ng. (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70, 191-221.

[8] Bansal, R. and A. Yaron. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *The Journal of Finance*, 59, 1481-1509.

[9] Bansal, R., D. Kiku and A. Yaron. (2010). Long Run Risks, the Macroeconomy, and Asset Prices. *American Economic Review -Papers and Proceeding*, 100(2), 1-5.

[10] Barsky, R.B. (1989). Why don't the prices of stocks and bonds move together? *American Economic Review*, 79, 1132-1145.

[11] Baele, L., G. Bekaert and K. Inghelbrecht. (2010). The determinants of stock and bond return comovements. *Review of Financial Studies* 23, 2374-2428.

[12] Beltratti, A. and R.J. Shiller. (1992). Stock prices and bond yields. Can their comovements be explained in terms of present value models? *Journal of Monetary Economics*, 30, 25-46.

[13] Benzoni, L., P. Collin-Dufresne and R.S. Goldstein. (2007). Portfolio choice over the life-cycle when the stock and labor markets are cointegrated. *Journal of Finance* 62, 2123–2167.

[14] Bouaddi, M. and A. Taamouti. (2013). Portfolio Selection in a Data-Rich Environment. *Journal of Economic Dynamics and Control*, 37(12), 2943–2962

[15] Brandt, M.W. and P. Santa-Clara. (2006). Dynamic portfolio selection by augmenting the asset space. *The Journal of Finance*, 61, 2187-2217.

[16] Brandt, M.W., P. Santa-Clara, R. Valkanov. (2009). Parametric portfolio policies: exploiting characteristics in the cross section of equity returns. *Review of Financial Studies*, 22, 3411-47.

[17] Campbell, J.Y. and J. Ammer. (1993). What moves the stock and bond markets? A variance decomposition for long term asset returns. *The Journal of Finance,* 48, 3-37.

[18] Campbell, J.Y., A. Sunderam and L. Viceira. (2013). Inflation bets or deflation hedges? the changing risks of nominal bonds, *Working Paper.*

[19] Carrière-Swallow, Y. and F. Labbé. (2013). Nowcasting With Google Trends in an Emerging Market. *Journal of Forecasting,* 32(4), 289-298.

[20] Cascon A., C. Keating and W. Shadwick. (2013). The omega function. *The Finance Development Centre Working Paper.*

[21] Choi, H. and H. Varian. (2012). Predicting the present with Google Trends. *The Economic Record*, 88(s1), 2-9.

[22] Choi, H. and H. Varian. (2009). Predicting initial claims for unemployment benefits, Google Inc., available at http://research.google.com/archive/papers/initialclaimsUS.pdf

[23] Clare, A. and I. Lekkos (2000). An analysis of the relationship between international bond markets. *Bank of England working papers* 123.

[24] Colacito, R. and M. M. Croce. (2010). The Short and Long Run Benefits of Financial Integration. *American Economic Review*, 100(2), 527-31.

[25] Colacito, R. and M. M. Croce. (2013). International Asset Pricing with Recursive Preferences. *The Journal of Finance* 68(6), 2651-2686.

[26] Da, Z., J. Engelberg and P. Gao. (2011). In Search of Attention. *Journal of Finance*, 66(5), 1461-1499.

[27] Della-Penna, N. and H. Huang. (2009). Constructing Consumer Sentiment Index for U.S. Using Google Searches. *University of Alberta Working Papers* 2009-26,

[28] Duffie, D., J. Pan and K. Singleton. (2000). Transform analysis and asset pricing for affine jump diffusions. *Econometrica*, 68 (6), 1343-1376.

[29] Engle, R.F. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business and Economic Statistics*, 20, 339-350.

[30] Engle, R.F., Ghysels, E. and Sohn, B. (2013). Stock Market Volatility and Macroeconomic Fundamentals. *Review of Economic and Statistics*, 95 (3), 776-797.

[31] Eraker, B. (2008). Affine general equilibrium models. *Management Science*, 54, 2068-2080.

[32] Farinelli, S. and L. Tibiletti. (2008). Sharpe thinking in asset ranking with one-sided measures. *European Journal of Operational Research*, 185, 1542-1547.

[33] Feunou, B., J-S. Fontaine, A. Taamouti, and R. Tedongap. (2014). Risk Premium, Variance Premium and the Maturity Structure of Uncertainty. *Review of Finance* 18, 219-269.

[34] Flannery, M.J. and A.A. Protopapadakis. (2002). Macroeconomic factors do influence aggregate stock returns. *The Review of Financial Studies* 15, 751–782.

[35] Hunter, D. and D. Simon. (2005). A conditional assessment of the relationships between the major world bond markets. *European Financial Management*, 11(4), 463-482.

[36] Ghysels, E., P. Santa-Clara, and R. Valkanov. (2006). Predicting volatility: getting the most out of return data sampled at different frequencies. *Journal of Econometrics*, 131 (1-2), 59-95.

[37] Ghysels, E., A. Sinko, and R. Valkanov. (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews*, 26 (1), 53-90

[38] Ginsberg, J., M. Mohebbi, R. Patel, L. Brammer, M. Smolinski and L. Brilliant. (2009). Detecting influenza epidemics using search engine query data. *Nature*, 457, 1012–14.

[39] Guzman, G. (2010). Internet search behavior as an economic forecasting tool: The case of inflation expectations. *MPRA Paper* 36512.

[40] Jones, C.M., O. Lamont, and R.L. Lumsdaine. (1998). Macroeconomic news and bond market volatility. *Journal of Financial Economics*, 47(3),.315-337.

[41] Karolyi, G.A. and R.M. Stulz. (1996). Why do markets move together? An investigation of US-Japan stock return comovements. *The Journal of Finance* 51, 951-986.

[42] Katzur, T. and L. Spierdijk. (2013). Stock returns and inflation risk: economic versus statistical evidence. *Applied Financial Economics*, 23(13), 1123-1136.

[43] Kenourgios, D. and A. Samitas. (2009). Financial market dynamics in an enlarged European Union. *Journal of Economic Integration*, 24, 197-221.

[44] Kholodilin K., M. Podstawski and B. Siliverstovs. (2010). Do Google Searches Help in Nowcasting Private Consumption?: A Real-Time Evidence for the US. *DIW Discussion Papers* 997.

[45] King, M.A., E. Sentana, and S.B. Wadhwani. (1994). Volatility and Links between National Stock Markets. *Econometrica* 62 (4), 901-933.

[46] Latoeiro, P., S. Ramos, and H. Veiga (2013). Predictability of stock market activity using Google search queries. *UC3M Discussion paper.*

[47] Longin, F. and B. Solnik. (1995). Is the correlation in international equity returns constant: 1960–1990?. *Journal of International Money and Finance,* 14, 3-26.

[48] Ludvigson, S. C. and S. Ng. (2009). Macro factors in bond risk premia. *The Review of Financial Studies*, 22, 5027-5067.

[49] McLaren, N. and R. Shanbhogue. (2011). Using internet search data as economic indicators. *Bank of England Quarterly Bulletin, Bank of England*, 51(2), 134-140.

[50] Perego, E. and W. Vermeulen. (2013). Macroeconomic determinants of European stock and government bond correlation: a tale of two regions. *CREA discussion paper* 13-08.

[51] Rangvid, J. (2006). Output and expected returns. *Journal of Financial Economics* 81, 595–624.

[52] Sargent, T.J. (2007). Long-Run Risks and Financial Markets. *Federal Reserve Bank of St. Louis Review*, 89(4), 301-03.

[53] Solnik, B., C. Boucrelle, and Y. Le Fur. (1996). International market correlation and volatility. *Financial Analysts Journal,* 52(5), 17-34.

[54] Sortino, F., R. van der Meer and A. Plantinga. (1999). The dutch triangle. *Journal of Portfolio Management*, 26, 50-57.

[55] Stock, J.H. and M.W. Watson. (2002a). Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics*, 20, 147-162.

[56] Stock, J.H., M.W. Watson. (2002b). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association*, 97, 1167-1179.

[57] Suhoy, T. (2009). Query indices and a 2008 downturn. *Bank of Israel Discussion Paper* 2009.06.

[58] Tamakoshi, G., Y. Toyoshima, and S. Hamori. (2012). A dynamic conditional correlation analysis of European stock markets from the prespective of the Greek sovereign debt crisis. *Economics Bulletin,* 32(1), 437-448.

[59] von Furstenberg, G. and B.N. Jeon. (1989). International stock price movements: Links and messages. *Brookings Papers on Economic Activity*, I, 125-167.

[60] Vosen, S. and T. Schmidt. (2011). Forecasting private consumption: survey-based indicators vs. Google trends. *Journal of Forecasting*, 30(6), 565-578.

[61] Wu, L and E. Brynjolfsson. (2013). The future of prediction: how Google searches foreshadow housing prices and sales. *NBER Chapters in: Economics of Digitization.*

COMPANION APPENDIX
FOR ONLINE PUBLICATION

In search of the determinants of European asset market comovement

A - Affine reduced-form models and cross-moments

- **Affine reduced-form models**
- **Cross-moments**

B -Measures of comovement: covariance and correlation

- B.1 Estimation of DCC model.
- B.2 Graphs of dynamic covariances and correlations

C - International risk factors

- C.1 Google keywords: top searches
- C.2 Graphs
- C.3 Orthogonalization of country specific factors
- C.4 Economic variables

D - Robustness and additional estimation results

- D.1 Non-parametric covariance
- D.2 DCC correlation
- D.3 Non-parametric correlation
- D.4 Within country stock and bond comovement
- D.5 Global and European factors
- D.6 Monthly frequency and Macro factors

E - Additional portfolio results

- E.1 Portfolio estimation
- E.2 Summary of portfolio weights
- E.3 Additional FT ratios

A Appendix: Affine reduced-form models and cross-moments

A.1 Affine reduced-form models

To characterize the relationship between international asset returns, we implicitly consider an endowment economy where the representative agent's preference ordering over consumption paths can be represented by a recursive utility function of the Epstein–Zin–Weil form

$$U_t = \left[(1-\delta) C_t^{(1-\gamma)/\theta} + \delta \left(E_t \left[U_{t+1}^{1-\gamma} \right] \right)^{1/\theta} \right]^{\theta/(1-\gamma)} \tag{15}$$

with θ defined as

$$\theta \equiv \frac{1-\gamma}{1-1/\psi},$$

where δ is the agent's subjective discount rate, ψ measures the elasticity of intertemporal substitution, and γ determines risk aversion and the preference for intertemporal resolution of uncertainty.

Following Eraker (2008) and Feunou et al. (2014), we assume that the joint dynamics of the consumption growth process, Δc_{t+1}, and of K state variables, X_{t+1}, in the economy has the following Laplace transform:

$$E_t \left[\exp \left(u_c \Delta c_{t+1} + v_x^\top X_{t+1} \right) \right] = \exp \left(F_0 \left(u_c, v_x \right) + X_t^\top F_X \left(u_c, v_x \right) \right), \tag{16}$$

where the scalar function $F_0 \left(u_c, v_X \right)$ and the vector function $F_X \left(u_c, v_x \right)$ describe the exogenous dynamics of the process $\left(\Delta c_{t+1}, X_{t+1}^\top \right)$ and must satisfy $F_0 (0,0) = F_X (0,0) = 0$. The vector X_t contains all variables underlying the state of the economy and explains asset returns across different countries.

The objective now is to use the above model to compute the covariances between the vectors of asset returns $r_{t+1}^{a_1} = \left(r_{t+1,1}^{a_1}, ..., r_{t+1,n}^{a_1} \right)^\top$ and $r_{t+1}^{a_2} = \left(r_{t+1,1}^{a_2}, ..., r_{t+1,n}^{a_2} \right)^\top$. To do so, we first derive the log-Laplace transform of the joint process $\left(r_{t+1}^{a_1}, r_{t+1}^{a_2} \right)^\top$. Before, using the standard Campbell–Shiller approximation $r_{t+1}^{a_i} = k_0^i + \omega_{t+1} k_1^i - \omega_t \iota + \Delta c_{t+1} \iota$, for $i = 1, 2$, the wealth-consumption ratio is given by

$$\omega_t = A_0 + A_X^\top X_t, \tag{17}$$

for values of ω_t near its steady-state [see Feunou et al. (2014)]. Next, we derive the log-Laplace transform of the joint process $\left(r_{t+1}^{a_1}, r_{t+1}^{a_2} \right)^\top$.

From Campbell-Shiller approximation, we have $\forall \left(u_{a_1}, u_{a_2} \right)^\top \in \mathbb{R}^n \times \mathbb{R}^n$,

$$\begin{aligned} & E_t \left[\exp \left(u_{a_1}^\top r_{t+1}^{a_1} + u_{a_2}^\top r_{t+1}^{a_2} \right) \right] \\ = \; & E_t \left[\exp \left(u_{a_1}^\top \left(k_0^{a_1} + \omega_{t+1} k_1^{a_1} - \omega_t \iota + \Delta c_{t+1} \iota \right) + u_{a_2}^\top \left(k_0^{a_2} + \omega_{t+1} k_1^{a_2} - \omega_t \iota + \Delta c_{t+1} \iota \right) \right) \right]. \end{aligned}$$

Now, using Equation (17) of wealth-consumption ratio, we obtain

$$
\begin{aligned}
& E_t\left[\exp\left(u_{a_1}^{\top} r_{t+1}^{a_1} + u_{a_2}^{\top} r_{t+1}^{a_2}\right)\right] \\
= \; & E_t\left[\exp\left(\begin{array}{c} u_{a_1}^{\top}\left(k_0^{a_1} + \left(A_0 + A_X^{\top} X_{t+1}\right) k_1^{a_1} - \left(A_0 + A_X^{\top} X_t\right)\iota + \Delta c_{t+1}\iota\right) \\ + u_{a_2}^{\top}\left(k_0^{a_2} + \left(A_0 + A_X^{\top} X_{t+1}\right) k_1^{a_2} - \left(A_0 + A_X^{\top} X_t\right)\iota + \Delta c_{t+1}\iota\right) \end{array}\right)\right] \\
= \; & \exp\left(u_{a_1}^{\top}\left(k_0^{a_1} + A_0 k_1^{a_1} - A_0\iota\right) + u_{a_2}^{\top}\left(k_0^{a_2} + A_0 k_1^{a_2} - A_0\iota\right) - X_t^{\top}\left(A_X \iota^{\top} u_{a_1} + A_X \iota^{\top} u_{a_2}\right)\right) \\
\propto \; & E_t\left[\exp\left(\left(u_{a_1}^{\top}\iota + u_{a_2}^{\top}\iota\right)\Delta c_{t+1} + \left(A_X k_1^{\top a_1} u_{a_1} + A_X k_1^{\top a_2} u_{a_2}\right)^{\top} X_{t+1}\right)\right].
\end{aligned}
$$

Under the condition (16), we have

$$
\begin{aligned}
& E_t\left[\exp\left(u_{a_1}^{\top} r_{t+1}^{a_1} + u_{a_2}^{\top} r_{t+1}^{a_2}\right)\right] \\
= \; & \exp\left(u_{a_1}^{\top}\left(k_0^{a_1} + A_0 k_1^{a_1} - A_0\iota\right) + u_{a_2}^{\top}\left(k_0^{a_2} + A_0 k_1^{a_2} - A_0\iota\right) - X_t^{\top}\left(A_X \iota^{\top} u_{a_1} + A_X \iota^{\top} u_{a_2}\right)\right) \\
\propto \; & \exp\left(F_{a_1,a_2,0}\left(u_{a_1}, u_{a_2}\right) + X_t^{\top} F_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right)\right),
\end{aligned}
$$

where

$$
\begin{aligned}
F_{a_1,a_2,0}\left(u_{a_1}, u_{a_2}\right) & \equiv F_0\left(u_{a_1}^{\top}\iota + u_{a_2}^{\top}\iota, A_X k_1^{\top a_1} u_{a_1} + A_X k_1^{\top a_2} u_{a_2}\right) & (18) \\
F_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right) & \equiv F_X\left(u_{a_1}^{\top}\iota + u_{a_2}^{\top}\iota, A_X k_1^{\top a_1} u_{a_1} + A_X k_1^{\top a_2} u_{a_2}\right). & (19)
\end{aligned}
$$

Thus, we have

$$
E_t\left[\exp\left(u_{a_1}^{\top} r_{t+1}^{a_1} + u_{a_2}^{\top} r_{t+1}^{a_2}\right)\right] = \exp\left(\bar{F}_{a_1,a_2,0}\left(u_{a_1}, u_{a_2}\right) + X_t^{\top} \bar{F}_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right)\right),
$$

where

$$
\begin{aligned}
& \bar{F}_{a_1,a_2,0}\left(u_{a_1}, u_{a_2}\right) = F_{a_1,a_2,0}\left(u_{a_1}, u_{a_2}\right) + u_{a_1}^{\top}\left(k_0^{a_1} + A_0 k_1^{a_1} - A_0\iota\right) + u_{a_2}^{\top}\left(k_0^{a_2} + A_0 k_1^{a_2} - A_0\iota\right) \\
& \bar{F}_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right) = F_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right) - A_X \iota^{\top} u_{a_1} + A_X \iota^{\top} u_{a_2}
\end{aligned}
\tag{20}
$$

with $F_{a_1,a_2,0}\left(u_{a_1}, u_{a_2}\right)$ and $F_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right)$ satisfying (18)-(19). Thus, the conditional cumulant-generating function is an affine function of the vector of state variables X_t :

$$
\Psi_t\left(u_{a_1}, u_{a_2}\right) = \log\left(E_t\left[\exp\left(u_{a_1}^{\top} r_{t+1}^{a_1} + u_{a_2}^{\top} r_{t+1}^{a_2}\right)\right]\right) = \bar{F}_{a_1,a_2,0}\left(u_{a_1}, u_{a_2}\right) + X_t^{\top} \bar{F}_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right). \tag{21}
$$

In the next subsection, we use the conditional cumulant-generating function in (21) to derive the cross-moments (covariance) between the vectors of asset returns $r_{t+1}^{a_1}$ and $r_{t+1}^{a_2}$.

A.2 Cross-moments

Using the conditional cumulant-generating function in (21), we have:

$$
\begin{aligned}
E_t\left[r_{t+1}^{a_1}\left(r_{t+1}^{a_2}\right)^\top\right] &= Cum\left(r_{t+1}^{a_1}, r_{t+1}^{a_2}\right) = \left.\frac{\partial^2 \Psi_t\left(u_{a_1}, u_{a_2}\right)}{\partial u_{a_1}\partial u_{a_2}}\right|_{u_{a_1}=u_{a_2}=0} \\
&= \left.\frac{\partial^2\left[\bar{F}_{a_1,a_2,0}\left(u_{a_1}, u_{a_2}\right) + X_t^\top \bar{F}_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right)\right]}{\partial u_{a_1}\partial u_{a_2}}\right|_{u_{a_1}=u_{a_2}=0} \\
&= \left.\frac{\partial^2\left[\bar{F}_{a_1,a_2,0}\left(u_{a_1}, u_{a_2}\right)\right]}{\partial u_{a_1}\partial u_{a_2}^\top}\right|_{u_{a_1}=u_{a_2}=0} + \left.\frac{\partial^2\left[X_t^\top \bar{F}_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right)\right]}{\partial u_{a_1}\partial u_{a_2}^\top}\right|_{u_{a_1}=u_{a_2}=0}.
\end{aligned}
$$

Observe that:

$$
\frac{\partial^2\left[X_t^\top \bar{F}_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right)\right]}{\partial u_{a_1}\partial u_{a_2}^\top} = \frac{\partial\left[\frac{\partial\left(X_t^\top \bar{F}_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right)\right)}{\partial u_{a_1}}\right]}{\partial u_{a_2}^\top}.
$$

For an n-dimensional vector x and any vectors u and $v(x)$ of $k \times 1$ dimension [see page 73 of Darrell A. Turkington (2002)'s Book], we have:

$$
\frac{\partial u^\top v(x)}{\partial x} = \frac{\partial v(x)}{\partial x} u.
$$

Thus,

$$
\frac{\partial\left(X_t^\top \bar{F}_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right)\right)}{\partial u_{a_1}} = \frac{\partial\left(\bar{F}_{a_1,a_2,X}\left(u_{a_1}, u_{a_2}\right)\right)}{\partial u_{a_1}} X_t.
$$

Now, observe that:

$$
\begin{aligned}
\frac{\partial^2 \left[X_t^\top \bar{F}_{a_1,a_2,X}\left(u_{a_1},u_{a_2}\right)\right]}{\partial u_{a_1}\partial u_{a_2}^\top} &= \frac{\partial \left[\frac{\partial\left(\bar{F}_{a_1,a_2,X}\left(u_{a_1},u_{a_2}\right)\right)}{\partial u_{a_1}} X_t\right]}{\partial u_{a_2}^\top} \\
&= \left[\frac{\partial \left[\frac{\partial\left(\bar{F}_{a_1,a_2,X}\left(u_{a_1},u_{a_2}\right)\right)}{\partial u_{a_1}} X_t\right]}{\partial u_{a_2}}\right]^\top, \text{ see page 69 of Turkington(2002)} \\
&= \left[\frac{\partial\ vec\left(\frac{\partial\left(\bar{F}_{a_1,a_2,X}\left(u_{a_1},u_{a_2}\right)\right)}{\partial u_{a_1}}\right)}{\partial u_{a_2}}\left[X_t \otimes I_n\right]\right]^\top, \text{ see page 73 of Turkington(2002)} \\
&= \left[X_t^\top \otimes I_n\right]\left(\frac{\partial\ vec\left(\frac{\partial\left(\bar{F}_{a_1,a_2,X}\left(u_{a_1},u_{a_2}\right)\right)}{\partial u_{a_1}}\right)}{\partial u_{a_2}}\right)^\top, \text{ see page 8 of Turkington(2002)} \\
&= X_t^\top \otimes \left(\frac{\partial\ vec\left(\frac{\partial\left(\bar{F}_{a_1,a_2,X}\left(u_{a_1},u_{a_2}\right)\right)}{\partial u_{a_1}}\right)}{\partial u_{a_2}}\right)^\top, \text{ see page 10 ofTurkington(2002)} \\
&= X_t^\top \otimes \frac{\partial\ vec\left(\frac{\partial\left(\bar{F}_{a_1,a_2,X}\left(u_{a_1},u_{a_2}\right)\right)}{\partial u_{a_1}}\right)}{\partial u_{a_2}^\top},
\end{aligned}
$$

where "*vec*" denotes the column stacking operator and "$\otimes$" is the Kronecker product. Hence

$$
E_t\left[r_{t+1}^{a_1}\left(r_{t+1}^{a_2}\right)^\top\right] = \beta_{a_1,a_2,0} + X_t^\top \otimes \beta_{a_1,a_2,X}.
$$

where

$$
\beta_{a_1,a_2,0} = \left.\frac{\partial^2 \left[\bar{F}_{a_1,a_2,0}\left(u_{a_1},u_{a_2}\right)\right]}{\partial u_{a_1}\partial u_{a_2}^\top}\right|_{u_{a_1}=u_{a_2}=0},\ \beta_{a_1,a_2,X} = \left.\frac{\partial\ vec\left(\frac{\partial\left(\bar{F}_{a_1,a_2,X}\left(u_{a_1},u_{a_2}\right)\right)}{\partial u_{a_1}}\right)}{\partial u_{a_2}^\top}\right|_{u_{a_1}=u_{a_2}=0}.
$$

B Appendix: Measures of comovement: covariance and correlation

B.1 DCC Estimation

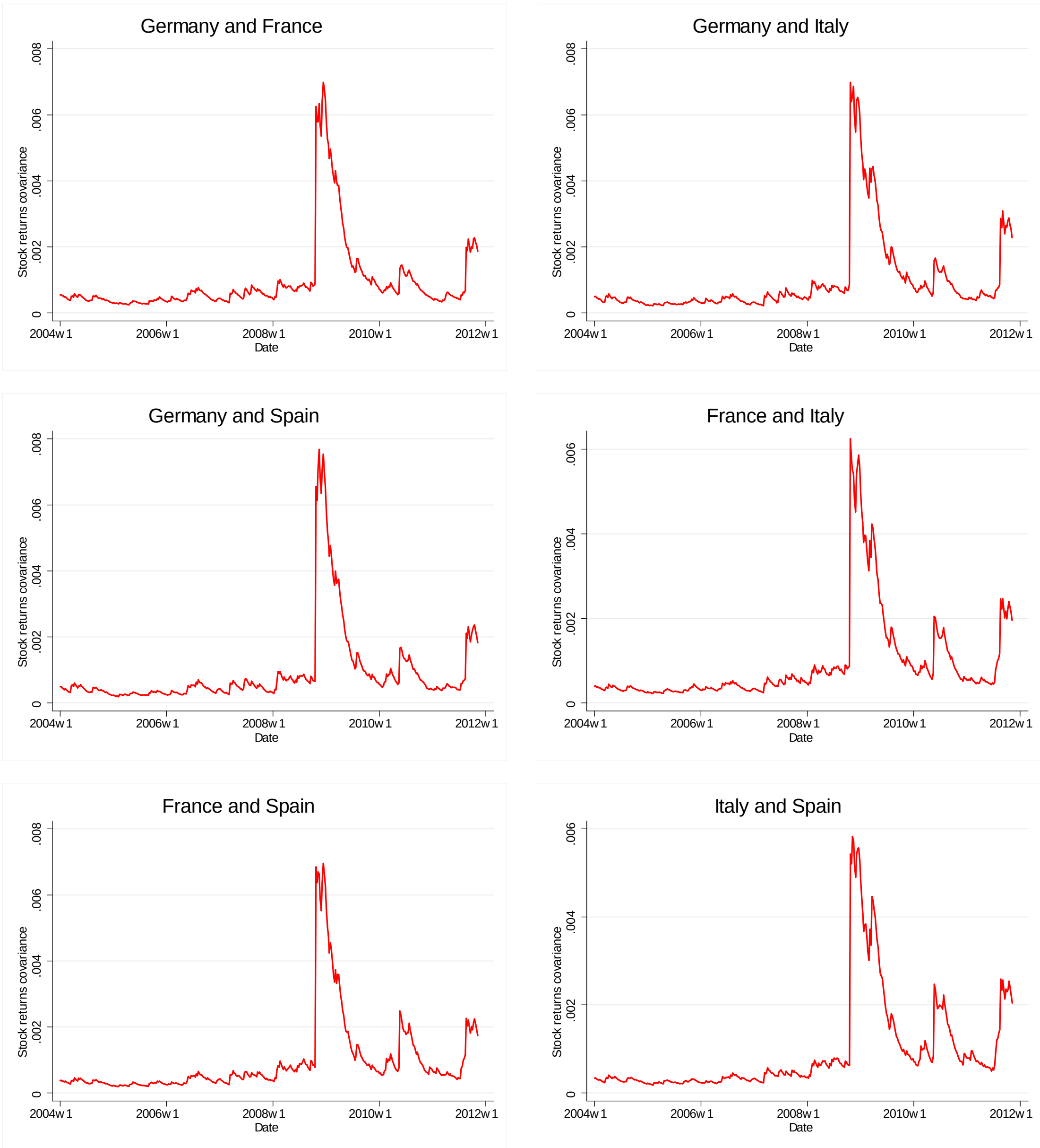
Table 9: Dynamic Conditional Correlation estimation of weekly returns

Unconditional Correlation		**Variable 1** ARCH	GARCH	**Variable 2** ARCH	GARCH	**Adjustment** λ_1	λ_2	**DF**
				A. Stocks returns				
$DE-FR$	0.92	0.086 (2.49)	0.889 (20.17)	0.090 (3.32)	0.899 (38.77)	0.042 (2.08)	0.933 (38.48)	6.05
$DE-IT$	0.85	0.118 (3.36)	0.870 (21.62)	0.089 (3.54)	0.904 (35.28)	0.081 (2.00)	0.513 (2.87)	6.42
$DE-SP$	0.83	0.118 (3.40)	0.870 (22.67)	0.088 (3.34)	0.902 (29.76)	0.054 (1.97)	0.898 (17.59)	7.01
$FR-IT$	0.91	0.098 (3.50)	0.876 (25.17)	0.086 (3.27)	0.893 (27.69)	0.013 (0.48)	0.834 (3.79)	8.77
$FR-SP$	0.87	0.120 (3.68)	0.872 (26.30)	0.092 (2.72)	0.892 (21.62)	0.026 (1.07)	0.936 (15.48)	7.81
$IT-SP$	0.88	0.093 (3.90)	0.893 (36.00)	0.080 (3.03)	0.899 (24.93)	0.032 (4.21)	0.968 (129.85)	6.57
				B. Bond returns				
$DE-FR$	0.89	0.118 (5.14)	0.921 (53.64)	0.112 (5.56)	0.926 (64.64)	0.091 (6.87)	0.883 (58.63)	4.22
$DE-IT$	0.46	0.180 (3.48)	0.855 (20.77)	0.147 (2.93)	0.874 (21.11)	0.309 (8.11)	0.617 (13.53)	4.65
$DE-SP$	0.48	0.172 (4.59)	0.897 (37.37)	0.153 (4.65)	0.902 (38.26)	0.332 (4.21)	0.597 (5.74)	3.84
$FR-IT$	0.66	0.122 (3.60)	0.877 (19.89)	0.134 (2.93)	0.863 (14.42)	0.169 (1.82)	0.787 (6.28)	5.07
$FR-SP$	0.67	0.129 (3.73)	0.896 (29.58)	0.118 (4.15)	0.904 (36.66)	0.312 (3.85)	0.587 (5.21)	4.42
$IT-SP$	0.88	0.160 (4.48)	0.863 (24.41)	0.140 (3.75)	0.883 (24.97)	0.253 (5.45)	0.647 (8.81)	4.17
				C. **Stock and Bond returns**				
DE	-0.48	0.191 (1.66)	0.734 (5.28)	0.113 (5.89)	0.891 (53.80)	0.032 (3.09)	0.949 (81.66)	9.93
FR	-0.37	0.108 (3.29)	0.867 (24.94)	0.112 (4.64)	0.882 (49.62)	0.018 (0.69)	0.888 (29.06)	11.26
IT	-0.03	0.100 (3.27)	0.894 (33.59)	0.121 (2.84)	0.846 (14.86)	0.096 (2.65)	0.796 (7.01)	7.52
SP	-0.03	0.097 (3.03)	0.891 (26.26)	0.109 (2.71)	0.870 (18.30)	0.141 (2.85)	0.610 (4.83)	8.21

Note: This table reports the results of the estimation of DCC models for stock and bond returns for different countries. λ_1 and λ_2 are the adjustment coefficients in Equation (*3*). Panel A shows the results of the correlations between stock returns in two different countries. Panel B shows the results for the correlations between bond returns in two different countries. Panel C shows the results for the correlations between stock and bond returns within the same country. DE, FR, IT, SP mean Germany, France, Italy, and Spain, respectively. Variable 1 means the first country (X) in the pairs X-Y, for X, Y= DE, FR, IT, SP, and Variable 2 means the second country (Y) in the pairs X-Y, for X, Y= DE, FR, IT, SP. In parenthesis is t-statistic of the coefficient. Sample of 512 observations from 2002w1 to 2011w45.

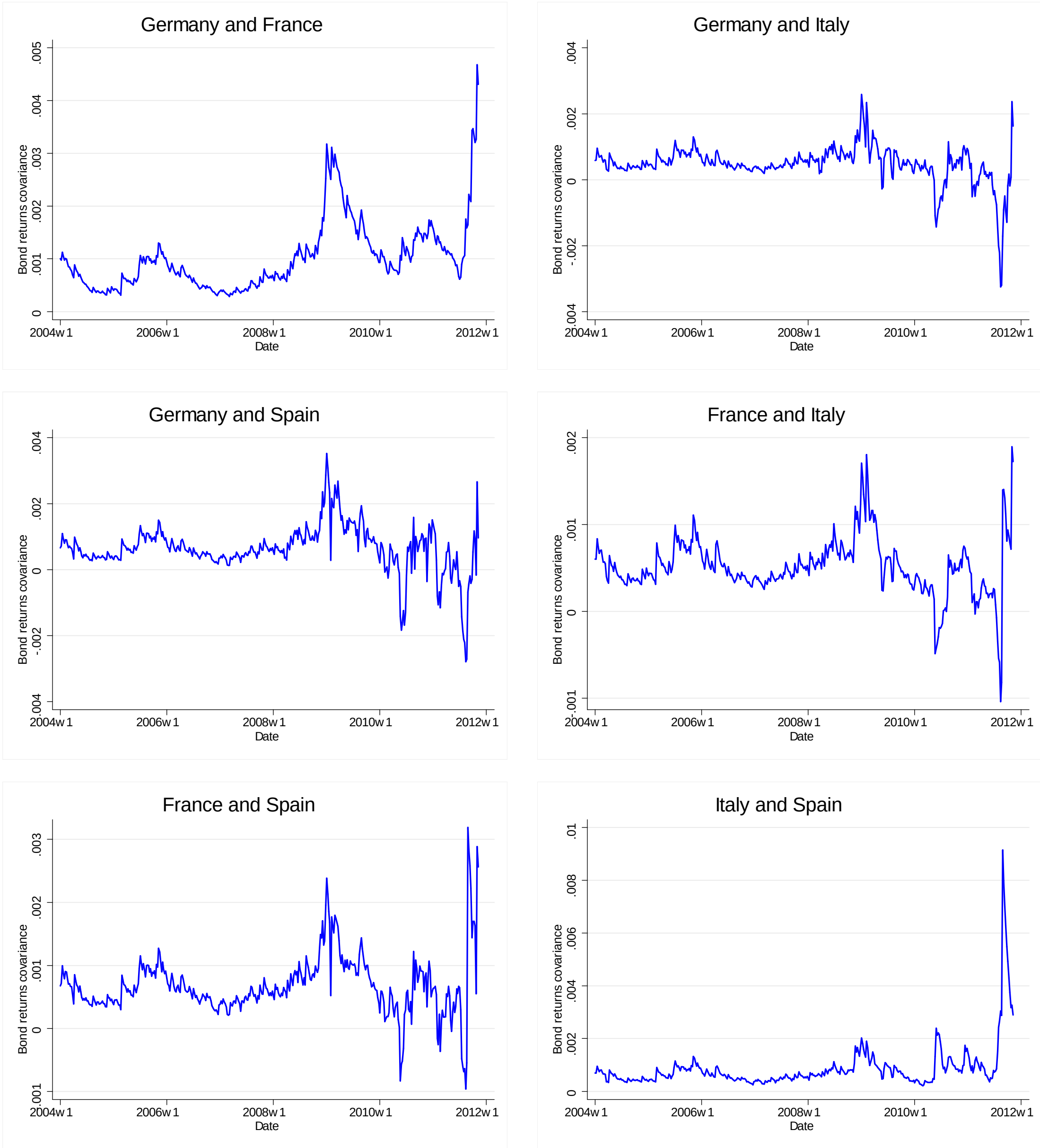
B.2 Graphs

Figure 1: Dynamic covariance between stock returns



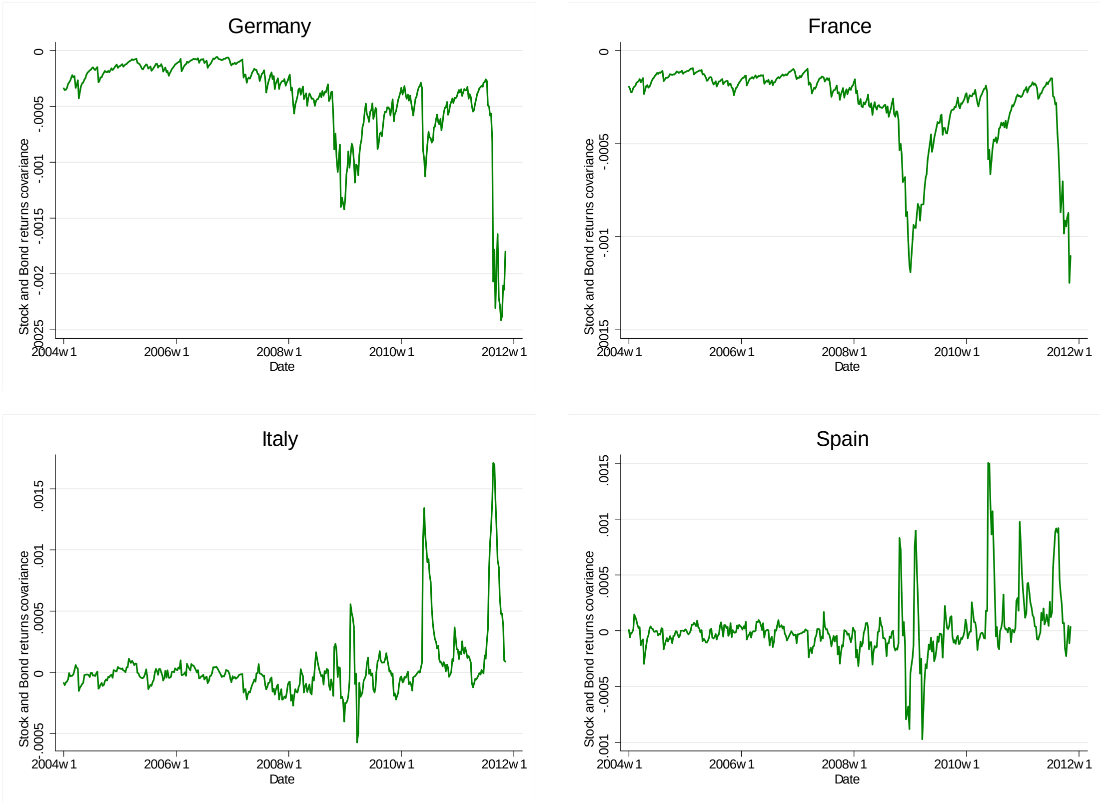
Note: Dynamic covariances between stock returns in different countries, filtered using the DCC model in Equation (3) estimated in Table 9, Panel A.

Figure 2: Dynamic covariance bond returns



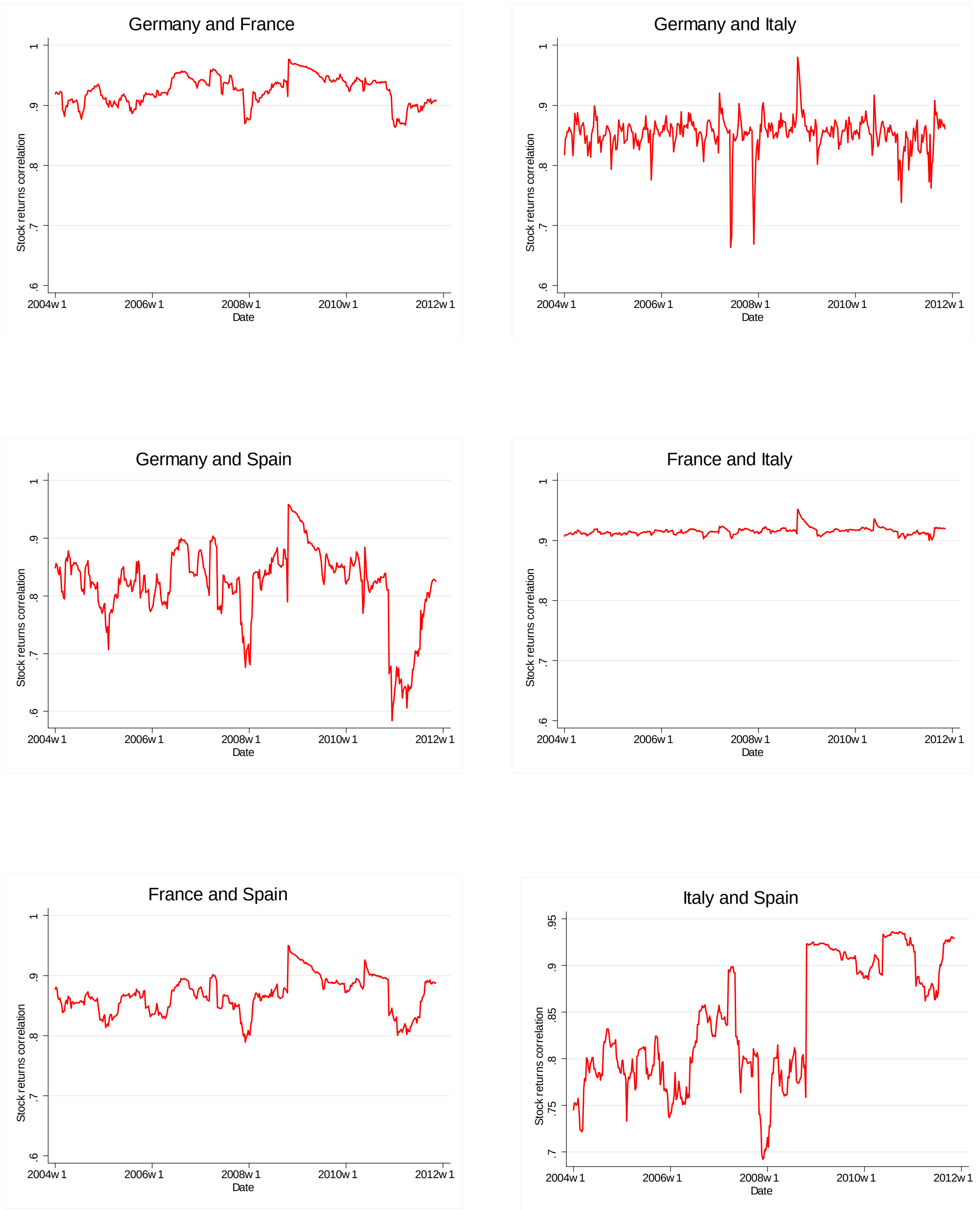
Note: Dynamic covariances between bond returns in different countries, filtered using the DCC model in Equation (3) estimated in Table 9, Panel B.

Figure 3: Dynamic covariance between stock and bond returns



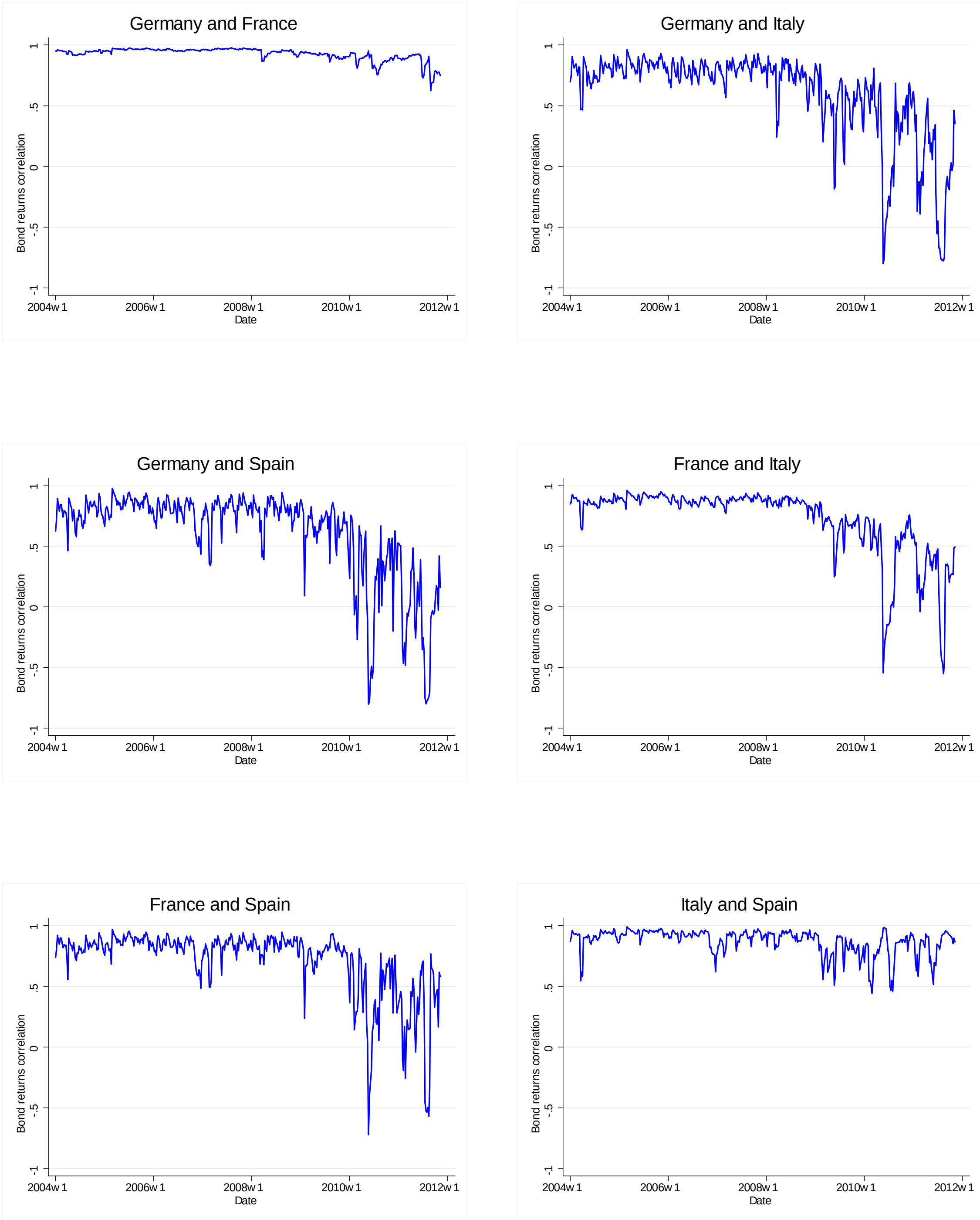
Note: Dynamic covariances between stock and bond returns within the same country, filtered using the DCC model in Equation (3) estimated in Table 9, Panel C.

Figure 4: Dynamic correlation between stock returns



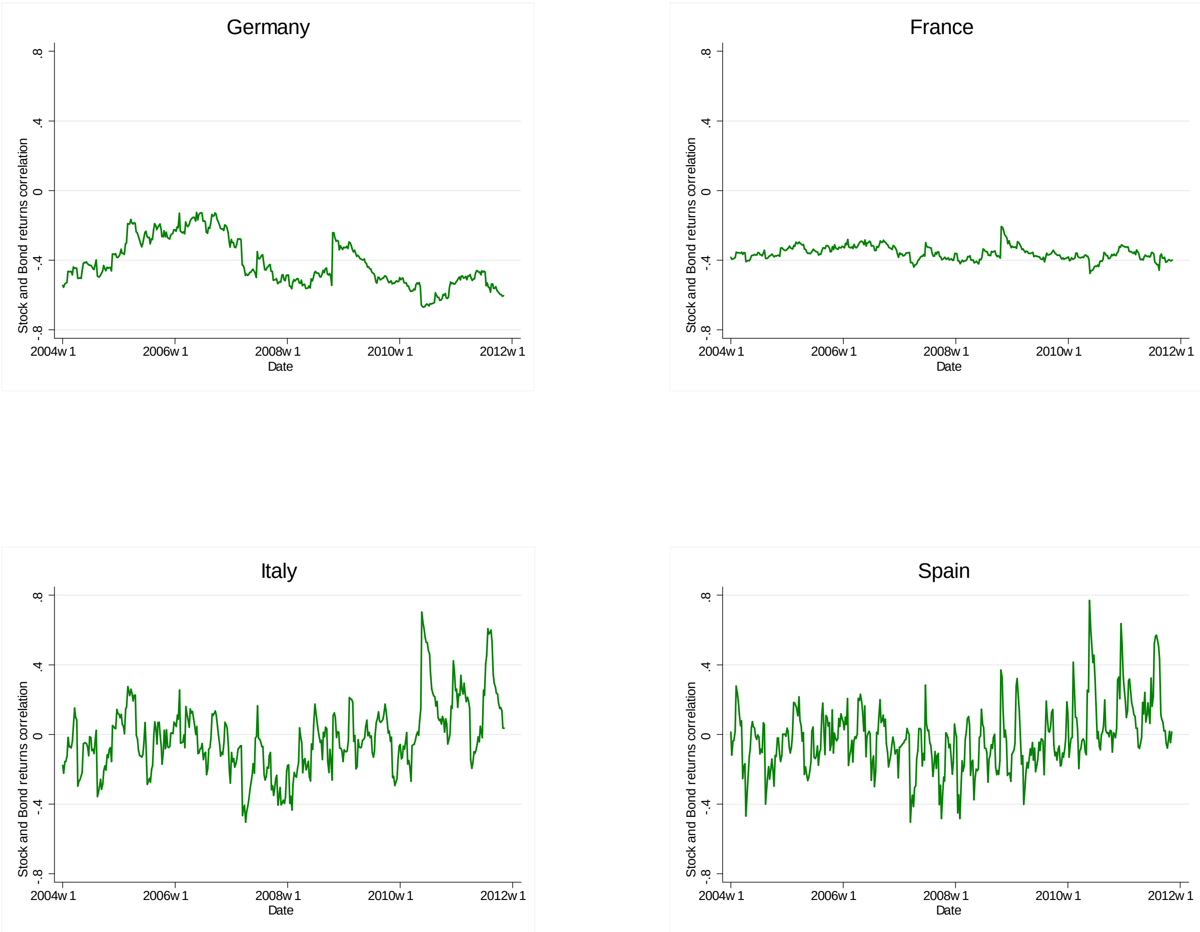
Note: Dynamic correlation between stock returns in different countries, filtered using the DCC model in Equation (3) estimated in Table 9, Panel A.

Figure 5: Dynamic correlation between bond returns



Note: Dynamic correlation between bond returns in different countries, filtered using the DCC model in Equation (3) estimated in Table 9, Panel B.

Figure 6: Dynamic correlation between stock and bond returns



Note: Dynamic correlation between stock and bond returns within the same country, filtered using the DCC model in Equation (3) estimated in Table 9, Panel C.

C Appendix: International Risk Factors

C.1 Google keywords: top searches

C.1.1 Jobs

- **Germany:** bewerbung, jobbörse, jobs, stellenangebote, ausbildung, job, lebenslauf, polizei, als, arbeit, praktikum, arbeitsamt, bewerbungsschreiben, suche, arbeitsagentur, stepstone, anschreiben, jobsuche, minijob, arbeitszeugnis.

- **France:** emploi, job, pole, cv, pole emploi, interim, anpe, stage, onisep, métier, offre emploi, metier, adecco, manpower, keljob, entretien, ouest job, anpe emploi, jobs, monster.

- **Italy:** lavoro, offerte lavoro, concorsi,offerte di lavoro, lavoro cerco, concorso, curriculum, gazzetta, curriculum vitae, gazzetta ufficiale, infojobs, curriculum europeo, lavoro roma, lavoro milano, lavorare, concorsi pubblici, jobrapido, curriculum vitae europeo, job, annunci lavoro.

- **Spain:** infojobs, trabajo, empleo, oposiciones, ofertas trabajo, infoempleo, ofertas empleo, infojob, ofertas de trabajo, ofertas de empleo, laboris, trabajar, loquo, curriculum, bolsa de trabajo, ett, trabajos, aragon, huesca, trabajo madrid.

- **US:** jobs, job, resume, salary, careers, career, interview, employment, indeed, cover letter, teacher, interview questions, careerbuilder, job search, nebraska, career builder, resumes, engineer, monster, job openings.

C.1.2 Construction and Maintainance

- **Germany:** fenster, holz, heizung, türen, schrauben, velux, kaminofen, friedberg, buderus, heizkörper, beton, kamin, dachfenster, bauunternehmen, viessmann, naturstein, ofen, granit, gewinde.

- **France:** porte, portail, chauffage, leroy merlin, castorama, poele, fenetre, construction, entreprise, edf, isolation, pierre, btp, radiateur, cheminée, bleu ciel, beton, volet, batiment, edf bleu ciel.

- **Italy:** ingegneria, porte, bagno, stufe, pellet, infissi, serramenti, condizionatori, tutto città, finestre, sanitari, stufe pellet, cemento, stufe a pellet, box doccia, daikin, climatizzatori, camini, scavolini.

- **Spain:** puertas, madera, construccion, aire acondicionado, acero, aluminio, herramientas, calderas, calefaccion, promociones, clickair, azulejos, caldera, carpinteria, chimeneas, casas madera, letra dni, roca, emt, reformas.

- **US:** construction, door, doors, concrete, wood, lumber, bridge, heat, water heater, air conditioner, home depot, granite, lowes, air conditioning, thermostat, furnace, screw, gis, bolt, sinks

C.1.3 Credit and Lending

- **Germany:** sparkasse, schufa, bafög, kredit, leasing, kreditkarte, ksk, baufinanzierung, credit, finanzierung, visa, mastercard, darlehen, kredite, schufa auskunft, kreissparkasse, ksk köln, american express, zinsrechner, lbb.

- **France:** credit, credit agricole, pret, crous, crédit, caf, simulation, cetelem, credit agricole nord, lcl, pret immobilier, cofidis, finaref, credit immobilier, lcl particulier, sofinco, taux immobilier, simulation pret, bourse, crédit agricole.

- **Italy:** postepay, mutui, mutuo, unicredit, cartasi, prestiti, banca unicredit, agos, euribor, prima casa, tasso, mutui on line, american express, prestito, carta di credito, paypal, findomestic, leasing, calcolo interessi, interessi legali.

- **Spain:** becas, hipoteca, mec, becas mec, tarjeta, hipotecas, ing, prestamos, beca, agencia tributaria, ibanesto, credito, cetelem, becas ministerio, creditos, personal, ebankinter, cofidis, simulador hipoteca, ministerio de educacion.

- **US:** chase, mortgage, wells fargo, loan, credit card, calculator, loans, capital one, american express, mortgage calculator, fafsa, credit report, chase online, credit cards, discover, loan calculator, bank of america, mortgage rates, free credit report, student loans.

C.1.4 Manufacturing

- **Germany:** emden, festo, maschinenbau, sps, roboter, bad neustadt, hersteller, metallbau, phoenix, sew, maβ, s7, phoenix contact, meinerzhagen, mfg, steuerung, weller, lenze, manufaktur.

- **France:** fabrication, fabricant, manutention, automate, festo, levage, platre, moulage, fabriquant, robotique, telemecanique, automatisme, polygone, uimm, hyperplanning, process, grafcet, sew, nailloux, plc.

- **Italy:** plc, nuova elettronica, il mulino, festo, bonfiglioli, guarnizioni, automazione, telemecanique, bft, reggiana, settore primario, acs, cereria, manufacturing, kit elettronica, settore secondario, sew, omron, pigna, sps.

- **Spain:** plc, festo, acs, telemecanique, automatas, sistema delta, elcorteingles viajes, omron, almussafes, averias telefonica, sps, sistema red, viajes corte inglés, automatizacion, telefonica averias telefono, neumatica, phoenix contact.

- **US:** manufacturing, manufacturers, acs, manufacturer, industrial revolution, plc, fabrication, allen bradley, mfg, simple machines, powder coating, ice cream maker, manufacture, casters, sew, the industrial revolution, rotation, caster, corning, weller.

C.1.5 Industrial Materials & Equipment

- **Germany:** pumpen, generator, baumaschinen, stahl, pumpe, hydraulik, bagger, wilo, danfoss, pneumatik, hoppe, valve, ksb, kran, busch, ventil, caterpillar, radlader, prien, erdgas.

- **France:** pompe, chaudiere, acier, hydraulique, cineville, passion, compresseur, rexel, cinéville, chaudière, roulement, groupe electrogene, ascenseur, chaudiere gaz, pompes, huile moteur, ien, caterpillar, pompe a eau, valve.

- **Italy:** tubi, pompe, gru, pompa, compressori, le gru, caterpillar, autodemolizioni, compressore, cappe, cappa, bomba, tornio, machine, turbina, idraulica, valve, carrelli elevatori, dieci, cuscinetti,

- **Spain:** bombas, gruas, bomba, grua, valvula, compresor, valvulas, mancomunidad, hidraulica, maquinaria, compresores, generador, generadores, caudal, carretillas, generator, caterpillar, molino, palas padel, valve.

- **US:** generator, valve, machine, grainger, propane, generators, crane, caterpillar, air compressor, tanks, lathe, machines, tubing, forklift, alternator, robin, boiler, cylinder, turbine, passion.

C.1.6 Fiscal policy news

- **Germany:** fellbach, inflationsrate, cpi, einkommen, rezession, steuerrechner, konjunktur, steuerrechner kfz, steuertabelle, grundeinkommen, schuldenuhr, inflation, wirtschaftskrise, betrag, durchschnittseinkommen, basel ii, ecb, inflationsrate deutschland, durchschnittseinkommen deutschland, wirtschaftswachstum.

- **France:** fiscalité, fiscale, revue fiduciaire, fiscal, cpi, rf, calcul brut net, convention fiscale, fiscalite, trichet, ecb, ministere des finances, tepa, rescrit, loi tepa, das2, rf social, fisc, stimulus, la fiscalité.

- **Italy**: valuta, valuta cambio, cambio, equitalia, giuliano, federalismo, gerit, equitalia gerit, federalismo fiscale, equitalia spa, condono, scandicci, esatri, esatri equitalia, cpi, condono fiscale, cambi, cambi valuta, equitalia sud, equitalia nord.

- **Spain:** caja cantabria, presupuestos, presupuesto, presupuestos generales, presupuestos del estado, presupuestos generales estado, abadia, fiscal, leopoldo, ley presupuestos, leopoldo abadia, abengoa, cajacantabria, ley de presupuestos, ley presupuestos generales, gasto, upyd, crisis ninja, rosa diez, presupuestos 2012.

- **US:** stimulus, checks, stimulus check, fiscal, tax credit, tax act, bailout, fiscal cliff, stimulus checks, stimulus package, economic stimulus, tax rebate, cpi, 2009 stimulus, us debt, irs stimulus, tax stimulus, debt clock, tax refund, budget cuts.

C.1.7 Economy news

- **Germany:** umsatz, marktwirtschaft, bip, wirtschaft, flug frankfurt, economist, survival, soziale marktwirtschaft, marktanteil, konkurrenz, bruttoinlandsprodukt, inflation, wiwo, flughafen hahn, frankfurt hahn, finanzkrise, bip deutschland, freie marktwirtschaft, treuhand, ifo.

- **France:** crise, vae, echos, les echos, pib, croissance, la crise, tribune, ocde, economist, financiere, la tribune, the economist, validation acquis, économie, crise financière, pib france, cnasea, validation des acquis, alternatives économiques.

- **Italy:** politica, inflazione, manovra, finanziaria, economist, finanziaria 2011, italia oggi, manovra 2011, manovra finanziaria, manovra finanziaria 2011, pil, the economist, crescita, bce, economia politica, politica italiana, tasso ufficiale, tasso sconto, pro capite, tasso inflazione.

- **Spain:** eleconomista, intereconomia, economist, rumasa, the economist, nueva rumasa, wyoming, pib, ocde, ruiz mateos, gran wyoming, intereconomia gaceta, subida irpf, subida ipc, radio intereconomia, intereconomia tv, actualidad economica, survival, solidaria, fondo monetario.

- **US:** depression, survival, economist, great depression, recession, the great depression, economy, the economist, price index, inflation, consumer price index, gdp, mccall, deficit, cpi, market crash, indymac, realtytrac, stock market crash.

C.1.8 Currency and Foreign exchange

- **Germany:** euro, währungsrechner, dollar, dollar euro, wechselkurs, kurs, umrechnung, pfund, währung, euro umrechnung, euro pfund, usd, currency, umrechner, euro kurs, euro wechselkurs, euro in dollar, dollarkurs, schweizer franken.

- **France**: euro, monnaie, euros, convertisseur, dollar, conversion, fx, dollar euro, currency, convertisseur monnaie, change, franc, usd, euros dollars, currency converter, exchange rate, conversion dollar, forex, la monnaie, euribor.

- **Italy:** euro, cambio, euro cambio, dollaro, dollaro euro, convertitore, valuta, cambio dollaro, cambio euro dollaro, sterlina, euro sterlina, convertitore euro, moneta, monete, cambio sterlina euro, cambio sterlina, convertitore valuta, dollari, lire, euro dollari.
- **Spain:** euro, cambio, conversor, euros, dolar, moneda, dolar euro, divisas, cambio euro, monedas, euros dolares, cambio dolar, divisas cambio, euro dolar cambio, conversor euros, libra, pesetas, currency, fx, dolares a euros.
- **US:** currency, dollar, usd, currency converter, exchange rate, euro, conversion, fx, currency exchange, dollar euro, exchange rates, us dollar, dolar, dollar exchange, dollar to euro, dollar rate, forex, dollar exchange rate, yen, foreign.

C.1.9 Property

- **Germany:** immobilien, immobilienscout, wohnung, immobilienscout24, haus, wohnungen, immoscout, immonet, ferienwohnung, wg, immowelt, scout immobilien, ferienhaus, sylt, 24, kroatien, immo, häuser, wohnungssuche, mietwohnungen.
- **France:** immobilier, location, maison, appartement, bon coin, immo, se loger, particulier, pap, neuf, ouest france, location appartement, vacances, espagne, seloger, agence immobiliere, gites, maison a vendre, orpi, particulier a particulier.
- **Italy:** affitto, case, immobiliare, casa, appartamenti, affitti, case vendita, tecnocasa, sardegna, case affitto, case in vendita, barcellona, immobili, agenzia immobiliare, locazione, affitto casa, case in affitto, agenzie immobiliari, agenzia del territorio, condominio.
- **Spain**: alquiler, pisos, fotocasa, en alquiler, idealista, inmobiliaria, casa, pisos alquiler, apartamentos, catastro, pisos en alquiler, alquiler de pisos, compraventa, inmobiliarias, vivienda, alquiler piso, catastro virtual, fincas, pisos en venta, alquiler apartamentos.
- **US**: apartments, real, homes, real estate, rent, for rent, house, rentals, houses, realty, florida, homes for sale, home, apartment, zillow, mls, houses for rent, realtor, houses for sale, condos.

C.1.10 Automobile industry

- **Germany:** vda, automobil, automotive, wiedemann, ilsfeld, automobilindustrie, wago, pierburg, wissmann, nsu, kreidler, apm, automobilzulieferer, visteon, konzern, zulieferer, vorhängeschloss, automobilwoche, kolbenschmidt.
- **France**: apm, auto distribution, autodistribution, ad distribution, wolseley, automotive, ad auto, visteon, sbm, ad auto distribution, autodistribution ad, first automobile, wago, vda, automobil, pierburg, chassi, general motors, wolseley france, wolsey.

- **Italy**: motorizzazione, motorizzazione roma, apm, vda, motorizzazione civile, roma motorizzazione civile, rottamazione, demolizione, fiat torino, codice autoradio, mirafiori, apm macerata, rottamazione auto, mirafiori torino, radiazione, motorizzazione roma laurentina, vda meteo, demolizione auto, motorizzazione laurentina, motorizzazione di roma.

- **Spain**: apm, cadenas, cadenas nieve, automocion, cotxes, cadenas de nieve, youtube apm, cadenas coche, cadenas para nieve, cadenas tela, visteon, castellana wagen, poner cadenas, cadenas nieve coche, cadenas para coche, cadenas de coche, cadenas textiles, cadenas ruedas, apm?, autosock.

- **US**: gm, general motors, gm stock, ford plant, uaw, sears automotive, apm, county line, automobiles, ford stock, visteon, auto industry, wards, ford motor company, first car, gm chrysler, model t, automotive industry, gm stock price, gm bailout.

C.2 Graphs

Figure 4: Google keyword searches indexes, United States

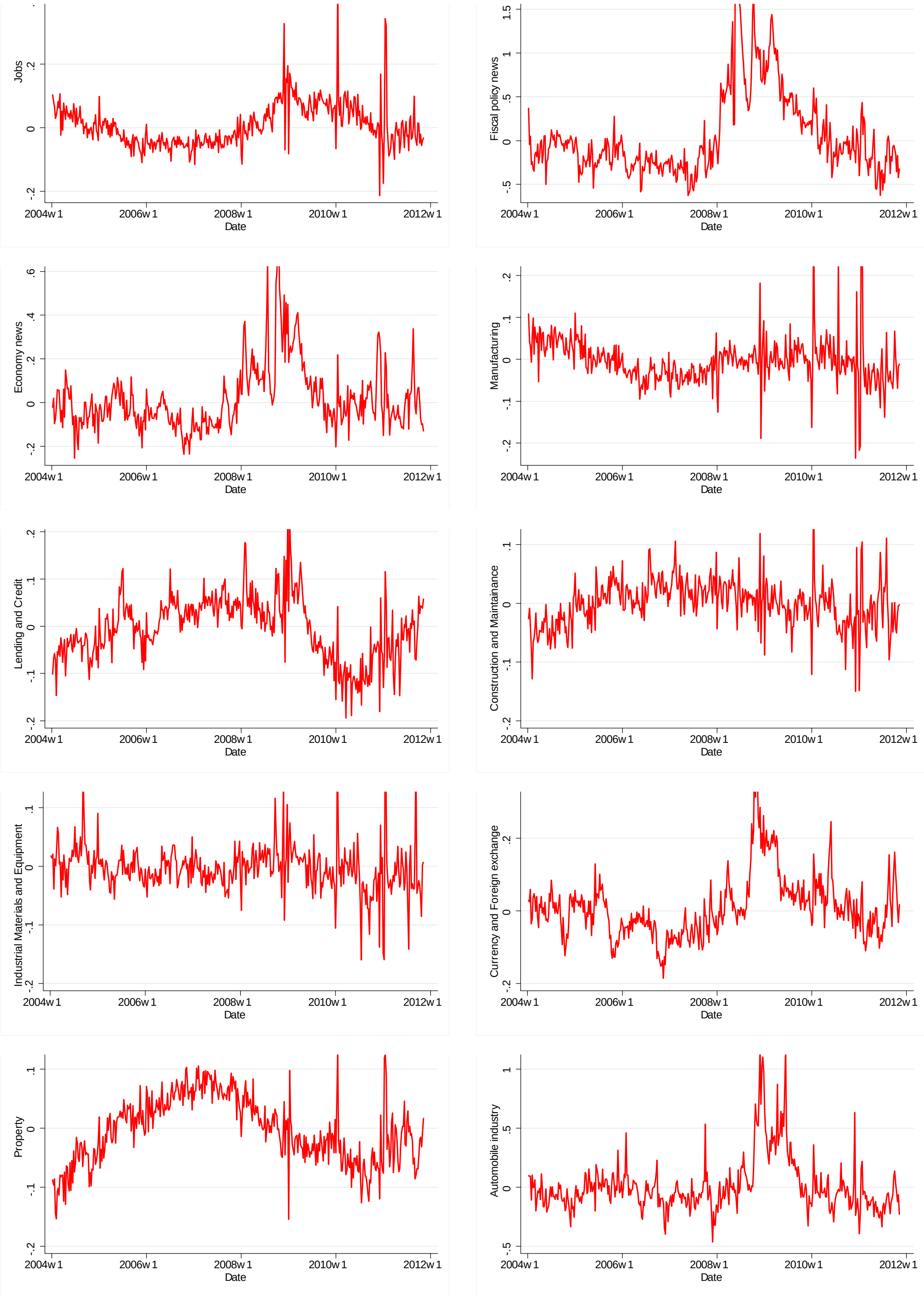
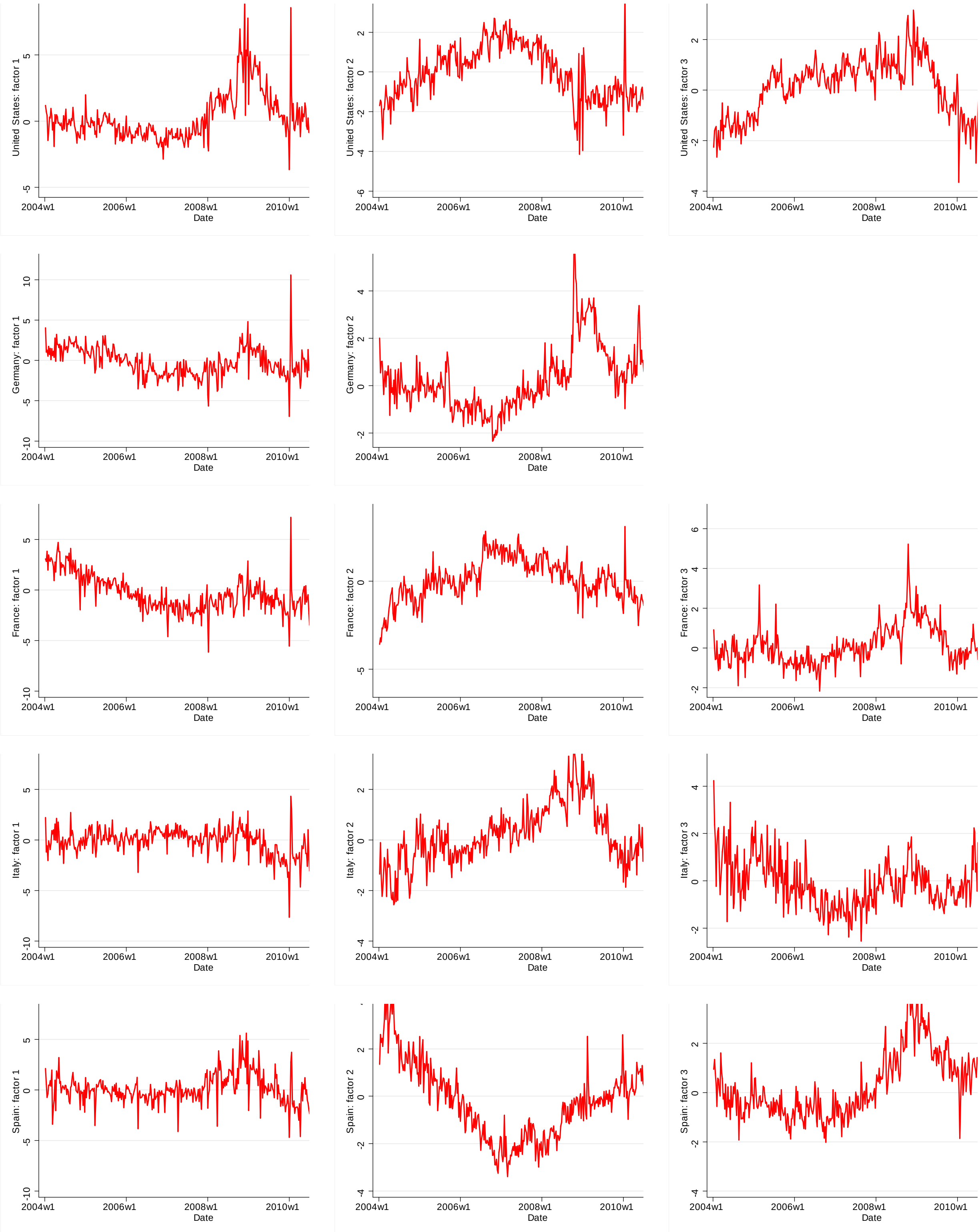


Figure 5: Estimated *Google* factors



Note: In this figure and for each country, the factors are extracted using principal component analysis.

C.3 Orthogonalization of country specific factors

Table 10: Orthogonalization of the country specific factors

Country	/ Factor	f_1^{us}		f_2^{us}		f_3^{us}		R^2
Germany	f_1^{de}	0.599	(14.20)**	-0.182	(-3.36)**	-0.824	(-11.67)**	0.43
	f_2^{de}	0.376	(22.11)**	0.504	(23.13)**	0.328	(11.52)**	0.71
France	f_1^{fr}	0.326	(7.40)**	-0.111	(-1.96)*	-0.902	(-12.24)**	0.31
	f_2^{fr}	-0.078	(-3.32)**	0.483	(15.98)**	-0.273	(-6.92)**	0.40
	f_3^{fr}	0.314	(17.64)**	0.165	(7.26)**	0.304	(10.19)**	0.50
Italy	f_1^{it}	0.295	(7.27)**	-0.501	(-9.63)**	-0.207	(-3.05)**	0.25
	f_2^{it}	0.300	(14.98)**	-0.033	(-1.27)	0.602	(17.93)**	0.54
	f_3^{it}	0.065	(2.65)**	0.185	(5.84)**	-0.119	(-2.89)**	0.09
Spain	f_1^{sp}	0.505	(14.28)**	-0.113	(-2.48)*	-0.015	(-0.25)	0.31
	f_2^{sp}	0.003	(0.12)	-0.464	(-15.41)**	0.677	(17.21)**	0.53
	f_3^{sp}	0.340	(17.19)**	-0.456	(-18.01)**	0.414	(12.52)**	0.63

Note: This table reports the estimation results of the country-specific factors on all the three US factors, see equation (6). Sample of 469 observations from 2004w1 to 2012w51. In parenthesis is t-statistic of the coefficient.** significant at 1 percent, * significant at 5 percent.

C.4 Description of economic variables

Table 11: Description of economic variables (Source: FRED database and Eurostat)

Code	Variable	Unit
United States		
M2	M2 Money Stock (weekly)	Billions of Dollars (logs)
COMPOUT	Commercial Paper Outstanding (weekly)	Billions of Dollars (logs)
WCOILWTICO	Crude Oil Prices: West Texas Intermediate (weekly)	Dollars per Barrel (logs)
CCSA	Continued Claims (Insured Unemployment) (weekly)	Number (logs)
UNRATE	Civilian Unemployment Rate	Percent
BOPGIMP	Imports of Goods, Balance of Payments Basis	Millions of dollars (logs)
BOPGSTB	Trade Balance Deficit: Goods and Services, Balance of Payments Basis	Millions of dollars (logs)
BUSINV	Inventories: Total Business	Millions of dollars (logs)
DGORDER	"Manufacturers' New Orders: Durable Goods	Millions of dollars (logs)
INDPRO	Industrial Production Index	Index (logs)
IPDCONGD	Industrial Production: Durable Consumer Goods	Index (logs)
IPMAN	Industrial Production: Manufacturing (NAICS)	Index (logs)
RSAFS	Retail and Food Services Sales	Millions of dollars (logs)
TCU	Capacity Utilization: Total Industry	Percent
TTLCONS	Total Construction Spending	Millions of dollars (logs)
TOTALSL	Total Consumer Credit Owned and Securitized, Outstanding	Billions of Dollars (logs)
COMPHAI	Housing Affordability Index	Index (logs)
PERMIT	New Private Housing Units Authorized by Building Permits	Thousands (logs)
SPCS20RSA	S&P Case-Shiller 20-City Home Price Index	Index (logs)
CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items	Index (logs)
PPIITM	Producer Price Index: Intermediate Materials: Supplies & Components	Index (logs)
NAPMNOI	ISM Manufacturing: New Orders Index	Index (logs)
AHETPI	Average Hourly Earnings of Production and Nonsupervisory Employees	Dollars per hour (logs)
PCEC96	Real Personal Consumption Expenditures	Billions of Dollars (logs)
PI	Personal Income	Billions of Dollars (logs)
Europe		
une_rt_m	Unemployment rate	Percent
prc_hicp_midx	Index of consumer prices (all items)	Index (logs)
sts_inprgr_m	Production in industry, Volume index of production, Manufacturing	Index (logs)

Note: This table describes the main economic variables used to interpret the Google factors, see Section 3.3.

Table 12: US factors and economic activity

Variable	f_1^{us}		f_2^{us}		f_3^{us}		R^2	Obs
M2 Money Stock	0.000	(1.11)	-0.000	(-0.02)	0.001	(1.97)*	0.01	469
Commercial Paper Outstanding	-0.002	(-3.80)**	-0.001	(-1.52)	-0.002	(-2.46)*	0.05	469
Crude Oil Prices	-0.003	(-3.08)**	-0.002	(-1.41)	-0.001	(-0.53)	0.02	469
Continued Claims	0.002	(5.41)**	-0.000	(-0.20)	0.002	(3.65)**	0.08	469
Unemployment Rate	0.041	(4.44)**	0.023	(2.12)*	0.059	(4.05)**	0.37	107
Imports of Goods	-0.005	(-2.82)**	0.000	(0.06)	-0.008	(-2.76)**	0.18	107
Trade Balance Deficit	-0.005	(-1.02)	-0.002	(-0.32)	-0.020	(-2.42)**	0.08	107
Inventories	-0.002	(-7.42)**	-0.000	(-1.42)	-0.002	(-4.14)**	0.51	107
New Orders: Durable Goods	-0.007	(-2.50)*	0.001	(0.19)**	-0.007	(-1.59)	0.11	107
Industrial Production Index	-0.002	(-3.93)**	-0.000	(-0.21)	-0.002	(-3.17)**	0.26	107
IPI: Durable Goods	-0.002	(-1.67)	-0.001	(-0.94)	-0.005	(-2.28)*	0.11	107
IPI: Manufacturing	-0.002	(-4.85)**	-0.000	(-0.83)	-0.003	(-4.06)**	0.36	107
Retail and Food Services Sales	-0.002	(-2.96)**	-0.000	(-0.45)	-0.002	(-2.43)*	0.17	107
Capacity Utilization	-0.127	(-3.45)**	0.030	(0.67)	-0.199	(-3.39)**	0.24	107
Total Construction Spending	-0.003	(-3.33)**	-0.001	(-0.76)	-0.003	(-1.96)*	0.18	107
Consumer Credit, Outstanding	-0.001	(-2.95)**	-0.001	(-1.62)	0.000	(0.63)	0.14	107
Housing Affordability Index	0.004	(2.03)*	-0.032	(-0.56)	0.003	(0.90)	0.06	107
New Building Permits	-0.010	(-2.96)**	0.004	(1.12)	-0.007	(-1.28)	0.12	107
Home Price Index	-0.002	(-3.81)**	-0.000	(-0.22)	-0.006	(-8.19)**	0.51	107
Consumer Price Index: Urban	-0.001	(-2.10)*	-0.000	(-0.90)	-0.000	(-0.47)	0.07	107
PPI: Intermediate Materials	-0.002	(-2.51)*	-0.001	(-0.74)	-0.002	(-2.04)*	0.14	107
New Orders Index	-0.051	(-8.11)**	-0.000	(-0.09)	-0.091	(-9.04)**	0.67	107
Average Hourly Earnings	0.000	(1.56)	-0.001	(-2.74)**	0.000	(1.85)	0.24	107
Real Consumption Expenditures	-0.001	(-3.02)**	-0.000	(-0.23)	-0.000	(-2.04)*	0.16	107
Personal Income	-0.001	(-2.53)*	-0.001	(-2.46)*	-0.001	(-2.06)*	0.20	107

Note: This table reports the estimation results of the regression of each US economic indicator in first-differences on all the three US factors. The first 4 economic indicators are weekly, with a sample of 469 observations from 2004w1 to 2012w51. The remaining indicators are monthly, with a sample of 107 from 2004m1 to 2012m11. In parenthesis is the t-statistic of the coefficient.** significant at 1 percent, * significant at 5 percent.

Table 13: Orthogonalized country-specific factors and economic activity

Variable	$\hat{f}_1^i$		$\hat{f}_2^i$		$\hat{f}_3^i$		R^2	Obs
Germany								
Unemployment rate	0.022	(3.52)**	0.048	(2.77)**			0.14	107
Consumer Price Index	-0.063	(-2.30)*	0.044	(0.61)			0.06	107
Industrial Production	-0.136	(-1.08)	-0.044	(-0.13)			0.01	107
France								
Unemployment rate	0.010	(1.53)	0.036	(2.76)**	-0.045	(-2.42)*	0.15	107
Consumer Price Index	-0.027	(-1.29)	0.040	(1.40)	0.017	(0.30)	0.03	107
Industrial Production	-0.029	(-0.27)	-0.310	(-1.50)	0.280	(0.95)	0.03	107
Italy								
Unemployment rate	0.018	(1.03)	0.012	(0.37)	0.022	(0.87)	0.02	107
Consumer Price Index	-0.012	(-0.18)	-0.071	(-0.59)	0.064	(0.67)	0.01	107
Industrial Production	-0.367	(-2.46)*	-0.064	(-0.24)	-0.012	(-0.06)	0.06	107
Spain								
Unemployment rate	0.062	(2.23)*	0.003	(0.12)	0.084	(1.96)	0.06	107
Consumer Price Index	-0.037	(-0.45)	-0.023	(-0.25)	-0.001	(-0.01)	0.01	107
Industrial Production	-0.355	(-1.65)	0.001	(0.00)	-0.191	(-0.57)	0.03	107

Note: This table reports the estimation results of the regression of the European economic indicators on all the extracted European countries-specific factors. The unemployment rate is in first differences, while the Consumer Price Index and Industrial Production are in growth rates. Sample of 107 observations from 2004m1 to 2012m12. In parenthesis is the t-statistic of the coefficient.** significant at 1 percent, * significant at 5 percent.

D Appendix: Robustness and additional results

D.1 Non-parametric covariance

Table 14: Cross-country stock market non-parametric covariance (20 weeks rolling window)

	DE – FR	**DE – IT**	**DE – SP**	**FR – IT**	**FR – SP**	**IT – SP**
			Global			
f_2^{us}	0.069 (19.09)**	0.070 (19.45)**	0.068 (17.20)**	0.082 (18.42)**	0.080 (16.05)**	0.078 (15.90)**
f_2^{us}	0.051 (10.62)**	0.053 (11.27)**	0.053 (10.13)*	0.064 (10.94)**	0.067 (10.24)**	0.070 (10.87)**
f_3^{us}	0.069 (11.40)**	0.070 (11.72)**	0.070 (10.54)**	0.080 (10.76)**	0.082 (9.89)**	0.079 (9.65)**
			Country			
$\hat{f}_1^{de}$	0.015 (2.61)**	0.006 (0.82)	0.010 (1.74)			
$\hat{f}_2^{de}$	0.043 (4.08)**	0.045 (4.46)**	0.021 (1.84)			
$\hat{f}_1^{fr}$	-0.017 (-2.79)**			-0.019 (-2.78)**	-0.011 (-1.42)	
$\hat{f}_2^{fr}$	0.008 (1.03)			0.016 (1.53)	0.008 (0.67)	
$\hat{f}_3^{fr}$	-0.028 (-2.91)**			-0.019 (-1.55)	-0.015 (-1.15)	
$\hat{f}_1^{it}$		0.002 (0.43)		0.014 (2.04)*		0.012 (1.55)
$\hat{f}_2^{it}$		0.000 (0.02)		0.014 (1.12)		0.004 (0.28)
$\hat{f}_3^{it}$		-0.011 (-1.67)		0.003 (0.34)		0.004 (0.43)
$\hat{f}_1^{sp}$			0.007 (1.21)		0.015 (1.94)*	0.001 (0.16)
$\hat{f}_2^{sp}$			0.002 (0.29)		-0.002 (-0.19)	-0.001 (-0.07)
$\hat{f}_3^{sp}$			0.036 (2.92)**		0.039 (2.74)**	0.043 (2.98)**
R^2	0.652 [0.621]	0.657 [0.639]	0.608 [0.589]	0.632 [0.617]	0.584 [0.566]	0.581 [0.568]
Obs	408	408	408	408	408	408

Note: This table reports the estimation of the regression of the non-parametric covariance of stock market returns in two countries on the global and country-specific factors, see Equation (7). The non-parametric covariance is calculated using Equation (4). The coefficients reported were multiplied by 10^3 for readability. Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression using only global factors.

Table 15: Cross-country bond market non-parametric covariance (20 weeks rolling window)

	DE – FR	*DE – IT*	*DE – SP*	*FR – IT*	*FR – SP*	*IT – SP*
			Global			
f_2^{us}	0.020 (8.44)**	0.016 (7.89)**	0.028 (11.20)**	0.010 (6.01)**	0.019 (10.30)**	0.007 (7.27)**
f_2^{us}	0.035 (10.82)**	0.003 (1.29)	0.013 (4.08)**	0.001 (0.38)	0.011 (4.56)**	0.007 (5.51)**
f_3^{us}	0.014 (3.56)**	0.004 (1.10)	0.013 (3.21)**	0.001 (0.26)	0.007 (2.36)*	0.001 (0.58)
			Country			
$\hat{f}_1^{de}$	0.003 (0.71)	-0.003 (-0.88)	-0.011 (-3.07)**			
$\hat{f}_2^{de}$	0.015 (2.19)*	0.005 (0.95)	-0.011 (-1.59)			
$\hat{f}_1^{fr}$	-0.005 (-1.33)			0.004 (1.63)	-0.001 (-0.40)	
$\hat{f}_2^{fr}$	-0.007 (-1.28)			0.005 (1.35)	-0.000 (-0.04)	
$\hat{f}_3^{fr}$	-0.009 (-1.32)			-0.005 (-1.18)	-0.021 (-4.30)**	
$\hat{f}_1^{it}$		-0.006 (-2.09)*		0.007 (-2.61)**		-0.001 (-0.75)
$\hat{f}_2^{it}$		-0.016 (-2.96)**		-0.010 (-2.09)*		-0.008 (-2.84)
$\hat{f}_3^{it}$		-0.017 (-4.52)**		-0.014 (-3.94)**		0.007 (3.82)**
$\hat{f}_1^{sp}$			0.017 (4.44)**		0.010 (3.39)**	0.005 (2.69)**
$\hat{f}_2^{sp}$			-0.003 (-0.61)		-0.001 (-0.12)	-0.010 (-4.89)**
$\hat{f}_3^{sp}$			0.036 (4.67)**		0.026 (4.96)**	0.006 (2.13)*
R^2	0.363 [0.348]	0.227 [0.141]	0.373 [0.289]	0.175 [0.094]	0.348 [0.266]	0.350 [0.209]
Obs	408	408	408	408	408	408

Note: This table reports the estimation of the regression of the non-parametric covariance of bond market returns in two countries on the global and country-specific factors, see Equation (7). The non-parametric covariance is calculated using Equation (4). The coefficients reported were multiplied by 10^3 for readability. Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression using only global factors.

D.2 DCC Correlation

Table 16: Cross-country stock market returns correlation

	$DE-FR$		$DE-IT$		$DE-SP$		$FR-IT$		$FR-SP$		$IT-SP$	
						Global						
f_2^{us}	0.004	(6.99)**	0.003	(3.85)**	0.013	(8.03)**	0.001	(7.46)**	0.007	(9.50)**	0.006	(3.84)*
f_2^{us}	0.002	(2.53)*	0.003	(2.91)**	0.004	(2.02)*	0.001	(5.22)**	0.007	(7.25)**	0.018	(8.65)*
f_3^{us}	0.006	(6.42)**	0.003	(1.99)*	0.010	(3.78)**	0.001	(3.79)**	0.004	(3.92)**	0.001	(0.48)
						Country						
$\hat{f}_1^{de}$	-0.001	(-1.53)	-0.001	(-1.09)	-0.006	(-2.41)*						
$\hat{f}_2^{de}$	0.003	(1.87)	-0.005	(-2.18)*	0.000	(0.03)						
$\hat{f}_1^{fr}$	-0.004	(-3.90)**					-0.001	(-5.50)**	-0.002	(-1.71)		
$\hat{f}_2^{fr}$	-0.002	(-1.99)*					0.000	(0.29)	0.003	(1.83)		
$\hat{f}_3^{fr}$	-0.007	(-4.45)**					-0.001	(-1.76)	-0.007	(-3.72)**		
$\hat{f}_1^{it}$			0.002	(1.78)			0.001	(3.61)**			-0.000	(-0.06)
$\hat{f}_2^{it}$			-0.001	(-0.53)			0.000	(0.49)			0.001	(0.27)
$\hat{f}_3^{it}$			0.001	(0.97)			0.000	(0.75)			-0.008	(2.87)**
$\hat{f}_1^{sp}$					0.010	(3.92)**			0.001	(0.85)	-0.012	(-4.16)**
$\hat{f}_2^{sp}$					0.007	(1.96)*			0.006	(3.46)**	0.004	(1.25)
$\hat{f}_3^{sp}$					0.006	(1.17)			0.003	(1.58)	-0.002	(-0.48)
R^2	0.321 [0.170]		0.096 [0.073]		0.245 [0.187]		0.262 [0.184]		0.363 [0.280]		0.247 [0.167]	
Obs	408		408		408		408		408		408	

Note: This table reports the estimation of the regression of the DCC correlation of stock market returns in two countries on the global and country-specific factors, see Equation (10). Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression using only global factors.

Table 17: Cross-country bond market returns correlation

	$DE-FR$		$DE-IT$		$DE-SP$		$FR-IT$		$FR-SP$		$IT-SP$	
						Global						
f_2^{us}	0.001	(0.46)	0.011	(1.18)	0.023	(2.54)*	0.008	(1.17)	0.016	(2.33)*	-0.003	(-1.06)
f_2^{us}	-0.014	(-8.20)**	-0.081	(-6.87)**	-0.071	(-5.90)**	-0.069	(-7.82)**	-0.050	(-5.39)**	-0.019	(-5.36)**
f_3^{us}	0.008	(3.51)**	0.026	(1.72)	0.045	(2.93)**	0.031	(2.75)**	0.025	(2.10)*	0.008	(1.91)*
						Country						
$\hat{f}_1^{de}$	-0.003	(-1.64)	-0.007	(-0.52)	-0.032	(-2.38)*						
$\hat{f}_2^{de}$	-0.002	(-0.41)	-0.049	(-1.95)*	-0.116	(-4.37)**						
$\hat{f}_1^{fr}$	0.005	(2.49)*					0.038	(3.71)**	0.033	(3.15)**		
$\hat{f}_2^{fr}$	-0.001	(-0.42)					0.032	(2.02)*	0.034	(2.05)*		
$\hat{f}_3^{fr}$	-0.008	(-2.27)*					-0.066	(-1.76)	-0.106	(-5.71)**		
$\hat{f}_1^{it}$			0.007	(0.55)			0.007	(0.67)			-0.001	(-0.19)
$\hat{f}_2^{it}$			-0.108	(-4.60)**			-0.047	(-2.49)*			-0.008	(-1.03)
$\hat{f}_3^{it}$			-0.053	(-3.19)**			-0.057	(-4.00)**			0.021	(4.17)**
$\hat{f}_1^{sp}$					0.075	(5.29)**			0.040	(3.68)**	0.012	(2.63)**
$\hat{f}_2^{sp}$					-0.037	(-1.92)*			0.032	(1.84)	-0.008	(-1.42)
$\hat{f}_3^{sp}$					0.037	(1.31)			0.023	(1.16)	-0.004	(-0.51)
R^2	0.214 [0.189]		0.216 [0.123]		0.217 [0.123]		0.279 [0.149]		0.214 [0.099]		0.165 [0.069]	
Obs	408		408		408		408		408		408	

Note: This table reports the estimation of the regression of the DCC correlation of bond market returns in two countries on the global and country-specific factors, see Equation (10). Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression using only global factors.

D.3 Non-Parametric Correlation

Table 18: Cross-country stock market returns non-parametric correlation

	$DE-FR$		$DE-IT$		$DE-SP$		$FR-IT$		$FR-SP$		$IT-SP$	
						Global						
f_2^{us}	0.006	(4.63)**	0.012	(6.07)**	0.018	(7.44)**	0.007	(4.08)**	0.012	(6.16)**	0.010	(5.16)**
f_2^{us}	0.003	(1.61)	-0.003	(-1.19)	0.001	(0.22)	-0.003	(-1.24)	0.004	(1.39)	0.009	(3.62)**
f_3^{us}	0.007	(3.19)**	0.008	(2.33)*	0.008	(2.14)*	0.015	(5.26)**	0.016	(4.74)**	0.001	(0.25)
						Country						
$\hat{f}_1^{de}$	-0.002	(-1.22)	-0.006	(2.16)*	-0.009	(-2.59)**						
$\hat{f}_2^{de}$	0.005	(1.38)	0.011	(2.10)*	0.002	(0.28)						
$\hat{f}_1^{fr}$	-0.003	(-1.45)					-0.015	(-5.77)**	-0.005	(-1.52)		
$\hat{f}_2^{fr}$	-0.000	(-0.01)					0.007	(1.76)	0.025	(5.27)**		
$\hat{f}_3^{fr}$	-0.011	(-3.42)**					-0.010	(-2.09)*	-0.031	(-5.85)**		
$\hat{f}_1^{it}$			0.005	(1.66)			0.008	(3.13)**			0.003	(1.02)
$\hat{f}_2^{it}$			-0.005	(-1.05)			0.005	(1.15)			0.005	(1.00)
$\hat{f}_3^{it}$			-0.004	(-1.00)			0.004	(1.08)			0.011	(3.11)**
$\hat{f}_1^{sp}$					0.007	(1.97)*			0.003	(1.10)	-0.005	(-1.61)
$\hat{f}_2^{sp}$					0.004	(0.91)			0.024	(4.81)**	-0.005	(-1.23)
$\hat{f}_3^{sp}$					-0.006	(-0.75)			-0.003	(-0.55)	-0.002	(-0.37)
R^2	0.144 [0.083]		0.134 [0.109]		0.171 [0.145]		0.208 [0.110]		0.292 [0.149]		0.150 [0.105]	
Obs	408		408		408		408		408		408	

Note: This table reports the estimation of the regression of the non-parametric correlation (20 weeks rolling window) of stock market returns in two countries on the global and country-specific factors, see Equation (10). Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression using only global factors.

Table 19: Cross-country bond market returns non-parametric correlation

	$DE-FR$		$DE-IT$		$DE-SP$		$FR-IT$		$FR-SP$		$IT-SP$	
						Global						
f_2^{us}	-0.002	(-2.05)*	0.021	(1.91)*	0.053	(4.65)**	0.003	(0.29)	0.037	(3.59)**	0.001	(0.13)
f_2^{us}	-0.010	(-7.58)**	-0.094	(-6.61)**	-0.066	(-4.39)**	-0.097	(-7.16)**	-0.061	(-4.49)**	-0.032	(-5.18)**
f_3^{us}	0.001	(0.83)	0.007	(0.41)	0.045	(2.36)*	-0.003	(-0.20)	0.024	(1.39)	0.000	(0.05)
						Country						
$\hat{f}_1^{de}$	-0.002	(-1.25)	-0.024	(-1.55)	-0.055	(-3.28)**						
$\hat{f}_2^{de}$	0.001	(0.27)	-0.008	(-0.26)	-0.075	(-2.26)*						
$\hat{f}_1^{fr}$	0.005	(2.71)*					0.027	(1.74)	0.034	(2.17)*		
$\hat{f}_2^{fr}$	0.003	(1.34)					0.039	(1.59)	0.057	(2.34)*		
$\hat{f}_3^{fr}$	-0.000	(-0.14)					-0.052	(-1.80)	-0.154	(-5.66)**		
$\hat{f}_1^{it}$			0.009	(0.54)			-0.014	(-0.88)			-0.010	(-1.35)
$\hat{f}_2^{it}$			-0.097	(-3.44)**			-0.075	(-2.59)*			-0.054	(-4.19)**
$\hat{f}_3^{it}$			-0.073	(-3.64)**			-0.104	(-4.74)**			0.018	(2.08)*
$\hat{f}_1^{sp}$					0.100	(5.65)**			0.061	(3.84)**	0.022	(2.64)**
$\hat{f}_2^{sp}$					-0.013	(-0.54)			0.063	(2.45)*	-0.012	(-1.24)
$\hat{f}_3^{sp}$					0.061	(1.70)			0.057	(1.95)*	-0.009	(-0.69)
R^2	0.157 [0.133]		0.181 [0.110]		0.200 [0.118]		0.197 [0.109]		0.197 [0.092]		0.154 [0.051]	
Obs	408		408		408		408		408		408	

Note: This table reports the estimation of the regression of the non-parametric correlation (20 weeks rolling window) of bond market returns in two countries on the global and country-specific factors, see Equation (10). Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression using only global factors.

D.4 Within country stock and bond comovement

Table 20: Stock and Bond market returns non-parametric covariance

	Germany	*France*	*Italy*	*Spain*
		Global		
f_1^{us}	-0.010 (-7.60)**	-0.009 (-8.71)**	0.003 (2.13)*	-0.006 (-4.18)**
f_2^{us}	-0.019 (10.53)**	-0.013 (10.10)**	0.005 (3.03)**	-0.003 (-1.67)
f_3^{us}	-0.004 (-1.67)	-0.003 (-1.61)	0.007 (3.36)**	-0.001 (-0.29)
		Country		
$\hat{f}_1^{de}$	0.007 (4.43)**			
$\hat{f}_2^{de}$	-0.003 (-0.95)			
$\hat{f}_1^{fr}$		0.006 (5.55)**		
$\hat{f}_2^{fr}$		0.002 (0.79)		
$\hat{f}_3^{fr}$		0.000 (0.14)		
$\hat{f}_1^{it}$			0.004 (2.63)**	
$\hat{f}_2^{it}$			0.000 (0.11)	
$\hat{f}_3^{it}$			0.007 (3.39)**	
$\hat{f}_1^{sp}$				-0.004 (-2.03)*
$\hat{f}_2^{sp}$				-0.013 (-4.69)**
$\hat{f}_3^{sp}$				-0.013 (-3.38)**
R^2	0.342 [0.306]	0.353 [0.300]	0.112 [0.066]	0.134 [0.043]
Obs.	408	408	408	408

Note: This table reports the estimation results of the regression of the non-parametric covariance (20 weeks rolling window) between bond and stock market returns in the same country on the global and country-specific factors, see Equation (8). The coefficients reported were multiplied by 10^3 for readability. Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression with only global factors.

Table 21: Stock and Bond market returns correlation (using DCC model)

	Germany		*France*		*Italy*		*Spain*	
				Global				
f_1^{us}	-0.004	(-1.33)	0.001	(1.19)	-0.005	(-0.94)	-0.010	(-1.98)*
f_2^{us}	-0.037	(-8.74)**	-0.002	(-1.80)	0.040	(6.12)**	0.024	(3.65)**
f_3^{us}	0.026	(4.88)**	0.006	(3.88)**	-0.023	(-2.77)**	-0.022	(-2.67)**
				Country				
$\hat{f}_1^{de}$	0.018	(4.67)**						
$\hat{f}_2^{de}$	-0.020	(-2.36)*						
$\hat{f}_1^{fr}$			0.004	(3.71)**				
$\hat{f}_2^{fr}$			0.001	(0.42)				
$\hat{f}_3^{fr}$			-0.009	(-3.55)**				
$\hat{f}_1^{it}$					-0.002	(-0.32)		
$\hat{f}_2^{it}$					0.040	(3.17)**		
$\hat{f}_3^{it}$					0.044	(5.14)**		
$\hat{f}_1^{sp}$							-0.024	(-3.21)**
$\hat{f}_2^{sp}$							-0.009	(-0.92)
$\hat{f}_3^{sp}$							0.002	(0.16)
R^2	0.276 [0.222]		0.114 [0.060]		0.194 [0.119]		0.101 [0.073]	
Obs.	408		408		408		408	

Note: This table reports the estimation results of the regression of the DCC correlation between bond and stock market returns in the same country on the global and country-specific factors. Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression with only global factors.

Table 22: Stock and Bond market returns non-parametric correlation

	Germany		*France*		*Italy*		*Spain*	
				Global				
f_1^{us}	-0.011	(-1.71)	-0.011	(-1.94)*	-0.003	(-0.35)	-0.027	(-3.40)**
f_2^{us}	-0.050	(-6.21)**	-0.041	(-5.47)**	0.027	(2.66)**	-0.003	(-0.30)
f_3^{us}	0.050	(4.88)**	0.052	(5.59)**	0.050	(3.93)**	0.006	(0.41)
				Country				
$\hat{f}_1^{de}$	0.049	(6.75)**						
$\hat{f}_2^{de}$	-0.002	(-0.11)						
$\hat{f}_1^{fr}$			0.027	(4.20)**				
$\hat{f}_2^{fr}$			0.003	(0.30)				
$\hat{f}_3^{fr}$			-0.018	(-1.25)				
$\hat{f}_1^{it}$					0.018	(1.83)		
$\hat{f}_2^{it}$					-0.001	(-0.06)		
$\hat{f}_3^{it}$					0.032	(2.38)*		
$\hat{f}_1^{sp}$							-0.045	(-3.71)**
$\hat{f}_2^{sp}$							-0.059	(-3.81)**
$\hat{f}_3^{sp}$							-0.071	(-3.29)**
R^2	0.237 [0.148]		0.190 [0.152]		0.074 [0.051]		0.111 [0.027]	
Obs.	408		408		408		408	

Note: This table reports the estimation results of the regression of the non-parametric correlation (20 weeks rolling window) between bond and stock market returns in the same country on the global and country-specific factors. Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression with only global factors.

D.5 Global and European factors

Table 23: Cross-country stock and bond market covariance (with European factors)

			Panel A: Stock Market			
	DE – FR	**DE – IT**	**DE – SP**	**FR – IT**	**FR – SP**	**IT – SP**
			Global			
f_2^{us}	0.342 (8.62)**	0.359 (8.88)**	0.354 (7.78)**	0.312 (9.37)**	0.333 (8.15)**	0.307 (8.88)**
f_2^{us}	0.280 (7.22)**	0.327 (8.41)**	0.306 (6.81)**	0.302 (9.42)**	0.319 (7.93)**	0.337 (10.38)**
f_3^{us}	0.367 (6.98)**	0.369 (6.88)**	0.369 (6.31)**	0.322 (7.07)**	0.341 (6.37)**	0.396 (6.30)**
			European			
$\hat{f}_1^{eu}$	0.002 (0.09)	0.006 (0.28)	0.008 (0.35)	-0.011 (-0.64)	-0.008 (-0.42)	-0.020 (-1.10)
$\hat{f}_2^{eu}$	0.024 (0.90)	0.023 (0.79)	0.034 (1.14)	0.032 (1.31)	0.048 (1.75)	0.039 (1.47)
$\hat{f}_3^{eu}$	0.122 (2.46)*	0.148 (2.90)**	0.125 (2.25)*	0.143 (3.23)**	0.138 (2.63)**	0.139 (2.92)**
R^2	0.58 [0.57]	0.58 [0.57]	0.56 [0.55]	0.60 [0.59]	0.57 [0.55]	0.58 [0.56]
Obs	408	408	408	408	408	408
			Panel B: Bond Market			
	DE – FR	*DE – IT*	*DE – SP*	*FR – IT*	*FR – SP*	*IT – SP*
			Global			
f_2^{us}	0.118 (6.61)**	0.086 (5.74)**	0.148 (7.53)**	0.013 (1.60)	0.081 (7.37)**	0.019 (1.01)
f_2^{us}	0.182 (9.74)**	-0.016 (-0.71)	0.048 (1.88)	-0.067 (-6.47)**	0.046 (3.08)**	0.108 (4.33)**
f_3^{us}	0.119 (4.43)**	0.087 (2.99)**	0.154 (4.47)**	0.028 (1.84)	0.084 (3.83)**	0.049 (1.13)
			European			
$\hat{f}_1^{eu}$	0.001 (0.04)	-0.005 (-0.40)	-0.012 (-0.90)	0.013 (2.04)*	0.021 (1.84)	0.061 (1.94)
$\hat{f}_2^{eu}$	-0.060 (-2.55)*	-0.010 (-0.34)	-0.022 (-0.73)	-0.002 (-0.15)	-0.050 (-2.08)*	-0.104 (-1.91)
$\hat{f}_3^{eu}$	-0.005 (-0.19)	-0.151 (-3.12)**	-0.155 (-2.80)**	-0.061 (-2.90)**	-0.055 (-1.68)	0.112 (2.02)*
R^2	0.35 [0.34]	0.19 [0.13]	0.28 [0.24]	0.21 [0.22]	0.24 [0.19]	0.12 [0.05]
Obs	408	408	408	408	408	408

Note: This table reports the estimation of the regression of the covariance of stock and bond market returns in two countries on the global and European-specific factors, see Equation (11). The coefficients reported were multiplied by 10^3 for readability. Sample of 408 observations from 2004w1 to 2011w45. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression using only global factors.

D.6 Monthly frequency and macro factors

Table 24: Cross-country stock market covariance at monthly frequency

	DE – FR	DE – IT	DE – SP	FR – IT	FR – SP	IT – SP
			Google (Monthly)			
f_2^{us}	0.392 (5.54)**	0.3979 (5.64)**	0.412 (5.32)**	0.350 (5.96)**	0.377 (5.34)**	0.343 (5.50)**
f_2^{us}	0.304 (4.34)**	0.378 (4.63)**	0.342 (4.17)**	0.338 (5.15)**	0.352 (4.66)**	0.388 (5.48)**
f_3^{us}	0.447 (5.59)**	0.494 (5.52)**	0.469 (4.87)**	0.413 (5.60)**	0.4.35 (4.80)**	0.405 (4.88)**
R^2	0.696	0.700	0.676	0.714	0.675	0.685
Obs	94	94	94	94	94	94
			Macro Variables			
ur	-0.912 (-3.15)**	-0.912 (-3.01)**	-0.919 (-2.82)**	-0.768 (-3.02)**	-0.788 (-2.63)**	-0.696 (-2.60)*
cpi	0.113 (3.62)**	0.118 (3.61)**	0.116 (3.25)**	0.104 (3.78)**	0.108 (3.30)**	0.100 (3.52)**
ip	-0.359 (-3.62)**	-0.374 (-3.67)**	-0.361 (-3.29)**	-0.320 (-3.70)**	-0.317 (-3.13)**	-0.307 (-3.45)**
R^2	0.402	0.422	0.359	0.445	0.367	0.452
Obs	94	94	94	94	94	94
			Macro Factors			
f_2^{uMacro}	-0.117 (-6.90)**	-0.140 (-7.87)**	-0.123 (-7.08)**	-0.129 (-8.69)**	-0.127 (-7.90)**	-0.152 (-9.95)**
f_2^{uMacro}	-0.378 (-5.89)**	-0.380 (-5.43)**	-0.377 (-5.17)**	-0.343 (-6.13)**	-0.360 (-5.39)**	-0.328 (-5.67)**
f_3^{uMacro}	-0.414 (-3.49)**	-0.439 (-3.36)**	-0.487 (-3.64)**	-0.374 (-3.62)**	-0.474 (-3.99)**	-0.397 (-3.81)**
R^2	0.655	0.5645	0.618	0.686	0.641	0.683
Obs	94	94	94	94	94	94

Note: This table reports the estimation of the regression of the covariance of stock market returns in two countries. at a monthly frequency on: i) the Google global factors, ii) three macroeconomic variables (unemployment rate in first differences, consumer price index and industrial production in log differences) and iii) three factors extracted from 20 macroeconomic monthly series listed in Table 12 in Appendix C.4. The coefficients reported were multiplied by 10^3 for readability. Sample of 64 observations from 2004m1 to 2011m10. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression using only global factors.

Table 25: Cross-country bond market covariance at monthly frequency

	DE – FR	DE – IT	DE – SP	FR – IT	FR – SP	IT – SP
			Google (Monthly)			
f_2^{us}	0.010 (1.67)	0.100 (1.97)	0.117 (1.83)	0.056 (1.97)	0.027 (0.67)	-0.072 (-0.87)
f_2^{us}	0.269 (4.89)**	0.008 (0.16)	0.147 (2.14)*	0.041 (1.47)	0.165 (3.30)**	0.290 (2.06)*
f_3^{us}	0.225 (2.92)**	0.165 (2.46)*	0.317 (3.42)**	0.149 (4.11)**	0.250 (4.61)**	0.256 (2.11)*
R^2	0.391	0.220	0.373	0.318	0.324	0.114
Obs	94	94	94	94	94	94
			Macro Variables			
ur	-0.141 (-1.11)	-0.403 (-3.21)**	-0.601 (-3.88)**	-0.216 (-2.75)**	-0.234 (-2.18)**	0.232 (1.41)
cpi	0.040 (3.89)**	0.030 (2.83)**	0.050 (3.73)**	0.021 (3.17)**	0.028 (3.64)**	0.009 (1.02)
ip	-0.103 (-2.19)*	-0.131 (-3.02)**	-0.217 (-4.22)**	-0.067 (-2.37)*	-0.085 (-2.28)*	0.724 (1.23)
R^2	0.411	0.222	0.301	0.137	0.112	0.167
Obs	94	94	94	94	94	94
			Macro Factors			
f_2^{uMacro}	-0.112 (-7.40)**	0.014 (0.92)	-0.007 (-0.39)	-0.002 (-0.21)	-0.026 (-1.92)	-0.078 (-3.31)**
f_2^{uMacro}	-0.075 (-1.44)**	-0.139 (-3.01)**	-0.227 (-4.80)**	-0.057 (-1.98)	-0.063 (-1.50)	-0.121 (1.53)
f_3^{uMacro}	-0.285 (-2.43)*	-0.007 (-0.07)	0.194 (0.18)**	-0.106 (-1.74)	-0.167 (-1.69)	-0.501 (-2.78)**
R^2	0.497	0.187	0.286	0.210	0.191	0.226
Obs	94	94	94	94	94	94

Note: This table reports the estimation of the regression of the covariance of bond market returns in two countries. at a monthly frequency on: i) the Google global factors, ii) three macroeconomic variables (unemployment rate in first differences, consumer price index and industrial production in log differences) and iii) three factors extracted from 20 macroeconomic monthly series listed in Table 12 in Appendix C.4. The coefficients reported were multiplied by 10^3 for readability. Sample of 64 observations from 2004m1 to 2011m10. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent. In square brackets is the R-squared of the regression using only global factors.

E Appendix: Additional portfolio results

E.1 Portfolio Estimation

Table 26: Google common factors portfolio, weekly

	Stock Market		Bond Market	
Portfolio	*Risk aversion=5*	*Risk aversion=8*	*Risk aversion=5*	*Risk aversion=8*
ϑ_0^{DE}	3.463**	2.304**	0.257	0.256**
	(16.40)	(19.34)	(1.87)	(3.17)
ϑ_0^{FR}	-1.930**	-1.161**	0.885**	0.617**
	(-6.17)	(-6.61)	(4.51)	(5.40)
ϑ_0^{SP}	1.594**	1.168**	-0.299**	-0.167**
	(9.95)	(12.36)	(-3.04)	(-2.94)
ϑ_1^{DE}	-1.399**	-0.864**	-1.379**	-0.891**
	(-14.93)	(-16.45)	(-27.13)	(-29.50)
ϑ_1^{FR}	0.736**	0.363**	1.528**	0.977**
	(7.18)	(6.20)	(21.73)	(23.29)
ϑ_1^{SP}	0.331**	0.252**	-0.604**	-0.385**
	(7.98)	(10.79)	(-14.91)	(-16.80)
ϑ_2^{DE}	-0.037	-0.085	0.572**	0.323**
	(-0.38)	(-1.52)	(5.40)	(5.18)
ϑ_2^{FR}	1.214**	1.062**	-0.657**	-0.376**
	(9.11)	(13.53)	(-4.72)	(-4.65)
ϑ_2^{SP}	-0.144	-0.104	1.012**	0.602**
	(-1.32)	(-1.60)	(15.46)	(15.49)
ϑ_3^{DE}	1.159**	0.583**	2.307**	1.485**
	(7.38)	(6.55)	(23.33)	(26.15)
ϑ_3^{FR}	-1.036**	-0.598**	-3.535**	-2.263**
	(-5.84)	(-5.94)	(-20.71)	(-22.76)
ϑ_3^{SP}	-0.334**	-0.082	1.276**	0.804**
	(-4.12)	(-1.69)	(16.86)	(17.69)
$\bar{r}$	5.3%	3.4%	4.6%	2.9%
$\sigma(r)$	0.121	0.088	0.169	0.110
Sharpe Ratio	0.435	0.393	0.275	0.266
VaR	-0.185	-0.137	-0.284	-0.186

Note: The table reports the estimated coefficients $\hat{\vartheta}$ of Equation (12), using GMM. The instruments used consist of 4 lags of $r_{j,t+1}, r_{j,t+1}f_{1,t,}^{us}, r_{j,t+1}f_{2,t}^{us}$ and $r_{j,t+1}f_{3,t,}^{us}$. The mean return, standard deviation, Sharpe ratio and Value-at-risk of the portfolio are reported in monthly frequency. Sample of 402 observations. In parenthesis is the t-statistic of the coefficient. ** significant at 1 percent, * significant at 5 percent.

E.2 Summary of portfolio weights

Table 27: Relation of stock and bond market weights with US macroeconomic variables

Variable	Mean	Marginal Regression					
		Unemployment rate		Consumer Price Index		Industrial Production	
Stock Market							
Risk aversion=5							
Germany	3.43	-4.470	(-4.21)**	1.673	(3.14)**	-0.248	(-7.01)**
France	-1.96	3.209	(2.47)*	-1.303	(-2.15)*	0.387	(11.93)**
Italy	-2.10	0.562	(0.79)	-0.046	(-0.13)	-0.173	(-7.74)**
Spain	1.60	0.698	(2.97)**	-0.323	(-2.82)**	0.033	(3.89)**
Risk aversion=8							
Germany	2.29	-3.147	(-4.81)**	1.081	(3.23)**	-0.156	(-7.03)**
France	-1.18	2.088	(2.16)*	-0.819	(-1.76)	0.285	(11.88)**
Italy	-1.29	0.141	(0.23)	0.015	(0.05)	-0.144	(-8.00)**
Spain	1.18	0.918	(5.58)**	-0.276	(-3.18)**	0.015	(2.21)*
Bond Market							
Risk aversion=5							
Germany	0.23	-0.682	(-086)	0.802	(2.11)*	-0.141	(-5.30)**
France	0.64	-0.685	(-0.62)	-0.767	(-1.44)	0.192	(5.21)**
Italy	0.30	0.604	(1.58)	-0.163	(-0.87)	-0.068	(-5.33)**
Spain	-0.18	0.763	(1.67)	0.128	(0.57)	0.017	(1.01)
Risk aversion=8							
Germany	0.23	-0.682	(-086)	0.802	(2.11)*	-0.141	(-5.30)**
France	0.64	-0.685	(-0.62)	-0.767	(-1.44)	0.192	(5.21)**
Italy	0.30	0.604	(1.58)	-0.163	(-0.87)	-0.068	(-5.33)**
Spain	-0.18	0.763	(1.67)	0.128	(0.57)	0.017	(1.01)

Note: This table reports the mean weight and the coefficient of the regression of the weights on three US macroeconomic variables. The weekly weights are aggregated at month frequency. The unemployment rate is in first differences, the Consumer Price Index and Industrial Production are in growth rates. Sample of 107 observations from 2004m1 to 2012m11. In parenthesis is the t-statistic of the coefficient.** significant at 1 percent, * significant at 5 percent.

Figure 6: Estimated weekly portfolio weights, stock market

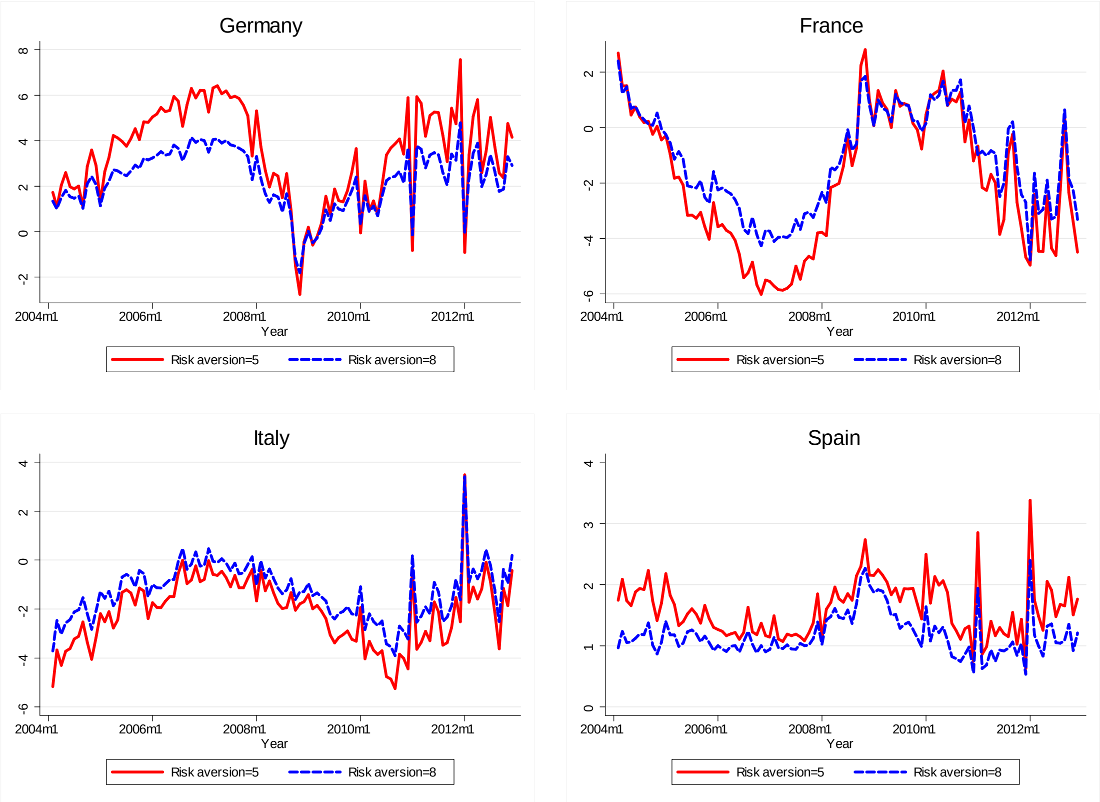
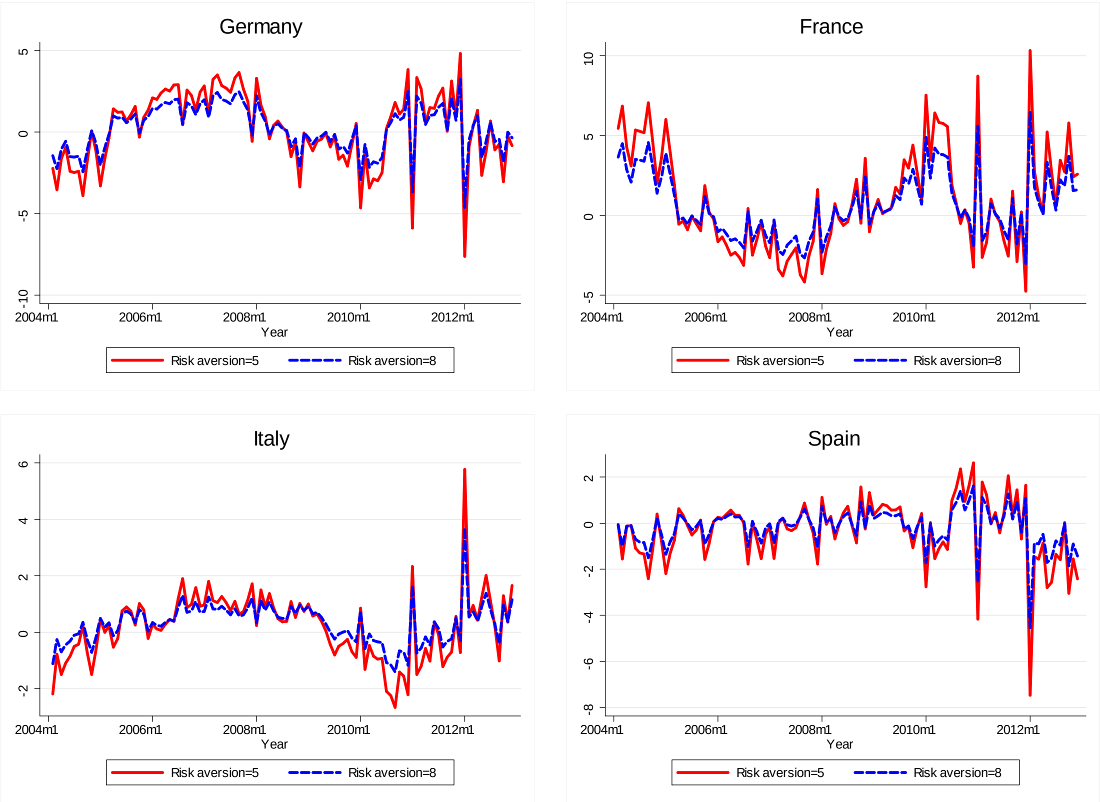


Figure 7: Estimated weekly portfolio weights, bond market



E.3 Portfolio performance: Additional FT ratios

Table 28: Farinelli and Tibileti ratio: Additional results

	Stock Market			Bond Market		
Portfolio	p=1,q=2	p=1,q=3	p=1,q=4	p=1,q=2	p=1,q=3	p=1,q=4
In-sample						
Equally weighted	0.524	0.406	0.342	0.700	0.588	0.518
Risk Aversion=5						
Constant weights	0.777	0.608	0.508	1.028	0.896	0.815
Google (weekly)	0.940	0.708	0.588	1.911	1.519	1.260
Google (monthly)	1.131	0.876	0.724	1.333	1.151	1.021
Risk Aversion=8						
Constant weights	0.780	0.603	0.508	0.865	0.761	0.694
Google (weekly)	0.783	0.606	0.515	1.605	1.306	1.100
Google (monthly)	1.037	0.806	0.665	1.302	1.128	1.008
Out-of-sample (1 year)						
Equally weighted	0.294	0.235	0.205	0.461	0.375	0.330
Risk Aversion=5						
Constant weights	0.294	0.235	0.205	0.531	0.434	0.382
Google (weekly)	0.825	0.694	0.634	0.427	0.368	0.334
Google (monthly)	0.445	0.364	0.322	0.224	0.186	0.166
Risk Aversion=8						
Constant weights	0.312	0.267	0.242	0.683	0.559	0.491
Google (weekly)	1.247	0.970	0.849	0.410	0.363	0.334
Google (monthly)	0.551	0.415	0.353	0.802	0.625	0.548

Note: This table reports the portfolio performance based on Farinelli and Tibiletti (2008) ratios defined in (14) for different values of p and q. The portfolios are constructed based on the weight function in (12) and the coefficients in Equation (13), estimated using the generalized method of moments. The instruments used consist of four lags of $r_{j,t+1}$, $r_{j,t+1}f_{1,t,}^{us}$, $r_{j,t+1}f_{2,t}^{us}$, and $r_{j,t+1}f_{3,t}^{us}$. The constant weights portfolios only estimate the constant term $\vartheta_{j,0}$. Two portfolios are constructed using Google search data at weekly and monthly frequencies (reported statistics are for monthly portfolio results). For the weekly estimation, the sample has 402 observations. For the monthly portfolio, the sample has 93 observations from 2004m2 to 2011m10. For the out-of sample portfolio, we show the summary of the portfolio for the last year of the sample (52 weeks or 12 months). We estimate Equation (12) up to week (month) t and compute the weights for the following week (month).