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THE US$/€ EXCHANGE RATE: STRUCTURAL MODELING AND FORECASTING DURING THE RECENT FINANCIAL CRISES

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The US$/€ exchange rate: Structural modeling and forecasting during the recent financial crises*

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Abstract

The paper investigates the determinants of the US$/€ exchange rate since its introduction in 1999, with a special focus on the recent subprime mortgage and sovereign debt financial crises. The econometric model is grounded on the asset pricing theory of exchange rate determination, which posits that current exchange rate fluctuations are determined by the entire path of current and future revisions in expectations about fundamentals. In this perspective, we innovate the literature by conditioning on Fama-French and Charart risk factors, which directly measures changing market expectations about the economic outlook, as well as on new financial condition indexes and a large set of macroeconomic variables. The macro-finance augmented econometric model has a remarkable in-sample and out of sample predictive ability, largely outperforming a standard autoregressive specification neglecting macro-financial information. We also document a stable relationship between the US$/€-Charart momentum conditional correlation (CCW) and the euro area business cycle, potentially exploitable also within a system of early warning indicators of macro-financial imbalances. Comparison with available measures of economic sentiments shows that CCW yields a more accurate assessment, signaling a progressive weakening in euro area economic conditions since June 2014, consistent with the sluggish and scattered recovery from the sovereign debt crisis and the new Greek solvency crisis exploded in late spring/early summer 2015.

Keywords: US$/€ exchange rate, asset pricing theory of exchange rate determination, macroeconomic and financial determinants, risk factors, subprime mortgage financial crisis, sovereign debt crisis, early warning indicators of macroeconomic and financial stress, forecasting, multivariate GARCH model.
JEL classification: E32, E44, G01, G15, C22.

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1 Introduction

Since its introduction in January 1999, the euro has rapidly gained the role of numeraire and medium of exchange for international transactions, as well as a store of value, even challenging the hegemony of the US$ as predominant international currency at a certain extent. Moreover, the bilateral US$/€ exchange rate is currently the most relevant currency pair in the foreign exchange market. Accurately forecasting the US$/€ exchange rate is then important for both practitioners and policy makers. Wieland and Wolters (2013), for instance, show that Central Bank policies in the US and Europe are well described by interest rate rules, where interest rates are set according to *forecasts* of inflation and economic activity, rather than outcomes. By influencing current account projections, as well as inflation and GDP growth predictions eventually, forecasting the US$/€ exchange rate is then of utmost relevance for the proper conduct of economic policy.

Surprisingly, little is known about the structural determinants of US$/€ exchange rate, particularly with reference to its fluctuations during the subprime mortgage and sovereign debt financial crises, as well as the post-crisis period. Most of the available evidence refers in fact to the pre-crisis period. For instance, Sartore et al. (2002) consider a structural econometric model for the real $US\$/€$ exchange rate in VECM form, using data from 1990 through 1999. They show that real long term interest rate spreads, foreign trade efficiency measures, fiscal policy differentials and commodity prices are relevant determinats of the currency. Other studies have provided evidence of convergence towards purchasing power parity (PPP) in the euro area. In particular, Lopez and Papell (2007), using panel data methods find evidence of PPP within the eurozone and between the eurozone and its main partners, over the period 1972 through 2001. Interestingly, the process of convergence towards PPP would have started before the introduction of the euro, following the currency crises in 1992 and 1993. Related articles by Koedijk et al al. (2004) and Schnatz (2007) also find evidence in favor of PPP over the periods 1973-2003 and 1980-2006, respectively. Evidence of nonlinearity in the adjustment of the $US\$/€$ exchange rate toward PPP is pointed out by Schnatz (2007) as well, as the speed of mean reversion in the US$/€ exchange rate would rise nonlinearly with the magnitude of the PPP deviation. The more recent paper of Camarero and Ordonez (2012) yields further evidence of nonlinearity in mean reversion toward the fundamentals represented by the productivity differential, over the period 1970-2009. The validity of the monetary model of exchange rate determination has also been directly assessed in recent studies. For instance, Nautz and Ruth (2005) find a theoretically coherent response of the nominal $US\$/€$ exchange rate to EA and US monetary disequilibria over the period 1981-2005. Chen et al. (2011) investigate cointegration of the $US\$/€$ with the fundamentals posited by the monetary exchange rate model, likewise money stocks, prices and real output, over the period 1994-2003. They show that both short-run (price stickiness) and long-run (secular growth) fundamentals affect the currency. Other studies have documented that hybrid versions of the monetary model yield a superior forecasting accuracy to the standard formulation. For instance, Chin and Moore (2011) investigate the period 1999-2007 and augment the monetary model fundamentals with order flow variables, consistent with the Evans–Lyons microstructure approach, in order to account for the potential role of innovations in public and private information, as measured by the net of buyer- over seller-initiated trades in the foreign exchange market. Beckmann et al. (2011) focus on the period 1975-2007 and augment the monetary model with imbalance measures, likewise the tradables over non-tradables price ratio and the trade balance, consistent with Harrod-Balassa-Samuleson effects and the portfolio model of exchange rate determination. Superior forecasting accuracy is also shown by Dal Bianco et al. (2012) for weekly US$/€ returns over the period 1998-2010, using a mixed-frequency econometric model based on monetary fundamentals quoted at the weekly and monthly frequencies.

In the light of the above results, the lack of empirical evidence for the recent subprime and sovereign debt financial crises surely is an important gap in the literature, which the paper aims to fill. In particular, we estimate a reduced form econometric model for both the conditional mean and variance of the $US\$/€$ exchange rate return, conditioning on a large set of macroeconomic and financial variables. The econometric model is grounded on the asset pricing theory of exchange rate determination, which posits that the current exchange rate depends on the present discounted value of the future stream of fundamentals. In the latter framework, exchange rate fluctuations are then accounted by news or revisions in expectations about fundamentals. We then innovate the literature by including in the information set, in addition to standard macroeconomic fundamentals, financial condition indexes and direct measures of changing market expectations about the economic outlook, as yield by risk factors likewise the five Fama and French (1993, 2015) factors and Charart (1997) momentum. Indeed, as recently shown by Morana (2014b) and Bagliano and Morana (2015), not only systematic fluctuations in the Fama-French and Charart factors are accounted by key macroeconomic and financial shocks, but, more importantly, their unexpected changes show signaling properties for macroeconomic prospects, consistent with their usual interpretation in terms of proxy for state variables capturing changes in the investment opportunity set.[1] A strict interlinkage between risk factor shocks and economic dynamics has also been documented by Morana (2014b), consistent with the recent strand of "news driven" business cycle literature, which has drawn attention to the role of abrupt changes in expectations in driving economic fluctuations (Beaudry and Portier, 2014).

To preview the results of the paper, we find that the estimated reduced form econometric models (AR-MF) are broadly in line with a hybrid version of the monetary model, where, in addition to monetary policy stance indicators, risk factors and (new) measures of EA and US financial conditions sizably contribute to the determination of the $US\$/€$ exchange rate. In particular, value, momentum and the EA financial condition index are robust predictors across subsamples. While risk factor data are publicly available, the employed financial condition indexes are an original contribution of the paper, and contain information related to anomalous interest rate spread fluctuations, given current economic conditions, and various measures of equity risk and economic policy uncertainty. Also importantly, measures related to real activity/labor market conditions, as well as to global imbalances, do matter for the determination of the $US\$/€$ exchange rate.

The AR-MF models show a remarkable in-sample predictive ability, accounting for 60% to 80% of $US\$/€$ returns variance, fivefold larger than for standard autoregressive models (AR) neglecting macro-financial information. This is not due to overfitting, as AR-MF models yield an average 30% reduction in $RMSFE$ out-of-sample and are

[1] As shown by Merton (1973), once shifts in the investment opportunity set are allowed for, the equity premium is determined by a multifactor model, in which risk is measured by state variables which capture unfavorable changes in the investment opportunity set, i.e., in the macroeconomic outlook. The success in predicting the equity premium of widely employed risk factors such as size, value and momentum factors is indeed explained in the light of the above argument.

forecast encompassing relatively to AR models.

Moreover, by assessing interlinkages in second-moments, we uncover a stable relationship between the US$/€-Charart momentum conditional correlation and the state of the EA economic cycle. In particular, we find that the latter dynamic conditional correlation becomes negative during periods of recession and positive during phases of economic expansion. A progressive weakening in EA economic conditions is then detected since June 2014, consistent with the sluggish and scattered recovery from the sovereign debt crisis which has eventually led the ECB to introduce the Quantitative Easing (QE) policy in January 2015. The negative $US\$/€$-momentum conditional correlation over the end of the sample is also consistent with the rising uncertainty concerning the survival of the EA itself, fueled by persistent solvency problems in Greece, newly exploded in late spring/early summer 2015. Comparison with standard indicators, likewise the Economic Sentiment Index computed by the European Commission, signalling improving economic conditions, yields clear-cut evidence of the value added and excess information content of the proposed index, exploitable also within a system of early warning indicators of macro-financial stress.

The rest of the paper is organized as follows. In Section 2 we provide theoretical insights on the role of risk factor information in exchange rate determination. In Section 3 we estimate a reduced form econometric model for the determination of the $US\$/€$ exchange rate and assess its forecasting performance over three different time spans, covering the subprime mortgage crisis, the sovereign debt crisis, and the post- sovereign debt crisis period, respectively. In Section 4 we assess second moment intertlinkages between $US\$/€$ exchange rate and risk factor returns. Finally, Section 5 concludes. Additional details about data, methodological contributions and empirical results are contained in the Online Appendix.

2 Exchange rate determination and risk factors

Consider the asset pricing model for exchange rate determination

$$e_t = \tilde{M}_t - \alpha \left[E_t e_{t+1} - e_t \right] \tag{1}$$

where e_t is the (log) exchange rate ($e_{US\$/€}$) at time period t, i.e., the value of one unit of local currency (€) in foreign currency units (US$), $E_t e_{t+1}$ is the exchange rate expected at time $t+1$ based on time t information, $\alpha > 0$ is a coefficient and $\tilde{M}_t$ represents the fundamentals at time period t.

Rearranging one has

$$e_t = \frac{1}{1-\alpha}\tilde{M}_t - \frac{\alpha}{1-\alpha}E_t e_{t+1}. \tag{2}$$

Forward iteration of (2), under the assumption of rational expectations, then yields

$$e_t = \frac{1}{1-\alpha}\sum_{\tau=0}^{\infty}\left(\frac{-\alpha}{1-\alpha}\right)^{\tau} E_t \tilde{M}_{t+\tau} \tag{3}$$

showing that the current exchange rate depends on the present discounted value of the future stream of fundamentals, where the discount rate is α.

From (3) it is then straightforward to conclude that what moves the exchange rate are news or revisions in expectations about fundamentals. In fact, the exchange rate expected at time t based on time $t-1$ information is

$$E_{t-1}e_t = \frac{1}{1-\alpha}\sum_{\tau=0}^{\infty}\left(\frac{-\alpha}{1-\alpha}\right)^{\tau} E_{t-1}\tilde{M}_{t+\tau} \tag{4}$$

and therefore its unexpected change is

$$\begin{aligned} e_t - E_{t-1}e_t &= \frac{1}{1-\alpha}\sum_{\tau=0}^{\infty}\left(\frac{-\alpha}{1-\alpha}\right)^{\tau}\left(E_t\tilde{M}_{t+\tau} - E_{t-1}\tilde{M}_{t+\tau}\right) && (5)\\ &= \frac{1}{1-\alpha}\sum_{\tau=0}^{\infty}\left(\frac{-\alpha}{1-\alpha}\right)^{\tau}\left(\tilde{M}_{t+\tau} - E_{t-1}\tilde{M}_{t+\tau}\right) && (6)\end{aligned}$$

where the term $E_t\tilde{M}_{t+\tau} - E_{t-1}\tilde{M}_{t+\tau}$ is the revision in expectations, equivalent to the surprise $\tilde{M}_{t+\tau} - E_{t-1}\tilde{M}_{t+\tau}$.

Various models can be described within the above general framework. For instance, the standard monetary model, under UIP and ex-ante PPP, would imply $\tilde{M}_t = -\beta(m_t - m_t^*) + \gamma(y_t - y_t^*)$, where m is the (log) nominal money supply, y is (log) real income, "*" denotes foreign variables, $\beta > 0$ and $\gamma > 0$ are coefficients, and the discount rate α bears the interpretation of interest rate semi-elasticity of money demand (Mussa, 1984). Hybrid versions of the monetary model can also be accommodated in the above framework, by including other macroeconomic and financial fundamentals, as well as directly modeling revisions in market expectations by means of risk factor innovations. In this respect, the available evidence shows that positive innovations to size and value factors reveal expectations of favorable changes in macroeconomic prospects, while the opposite holds for positive innovations to momentum (Morana, 2014b). The rationale is that small, poorly collateralized firms have limited access to external capital markets and are more vulnerable than large firms to adverse changes in credit conditions. Improved credit and, in general, macroeconomic prospects may then be associated with a rise in the profitability of small stocks, resulting in a higher size factor. A positive size innovation can then be interpreted as signaling improved expected credit market and general macroeconomic conditions. Similarly, firms with high book-to-market ratios are likely to suffer more from a higher debt burden and be more vulnerable to adverse changes in monetary policy and interest rates. Improved economic conditions may then be associated with higher profitability of value stocks, resulting in a larger value factor. A positive value innovation may then reveal expectations of favorable changes in macroeconomic conditions and investment opportunities. Moreover, if firms with stronger fundamentals outperform firms with weaker fundamentals during economic downturns and fundamentals are persistent and reflected in stock returns, positive momentum should be observed during recessions; a positive innovation to momentum could then reveal adverse changes in the economic outlook. Consistent empirical evidence is provided by Morana (2014b).[2]

[2] As shown by Morana (2014b), positive size and value shocks are followed by positive and persistent responses of real activity and a rise in the price of other real (house) and financial assets (long-term bonds, with a corresponding decrease in the term spread); a positive shock to momentum is followed by a contraction in real activity and a temporary increase in liquidity due to an expansionary change in the monetary policy stance, as well as by a "flight to safety", i.e., portfolio rebalancing towards short-term securities (with a decrease in the short rate), and away from stocks, housing, and long-term securities, leading to declines in their prices.

3 Structural determinants of the $US\$/€$ exchange rate

Our information set is monthly and spans the period 1999:1 through 2015:6. The (log) nominal $US\$/€$ exchange rate ($e_{\$/€}$) yields the value of 1 € in US$. The dependent variable is the nominal $US\$/€$ exchange rate log-return ($\Delta e_{\$/€}$); the set of conditioning variables is composed of two measures of economic activity, i.e., industrial production ($g_{I,€\text{-}\$}$) and real GDP ($g_{€\text{-}\$}$) growth rate differentials; the unemployment rate differential in changes ($u_{€\text{-}\$}$), as an indicator of relative labor market conditions; two measures of the monetary policy stance, i.e., the excess real money balance growth rate differential ($em_{€\text{-}\$}$) and the 3-month Libor rate differential ($li_{€\text{-}\$}$); the CPI inflation rate differential ($\pi_{€\text{-}\$}$), the EA current account balance ($bp_{€}$) and the US trade balance ($bp_{\$}$) in changes; nominal returns on oil ($o_{\$}$) and gold ($gd_{\$}$) prices, as well as on a non-energy commodities price index ($c_{\$}$); the US Fama-French size ($smb_{\$}$), value ($hml_{\$}$), market ($mkt_{\$}$), profitability ($rmw_{\$}$) and investment ($cma_{\$}$) factors, as well as Carhart momentum ($mom_{\$}$). We also include two newly proposed financial condition indexes ($fc_{€}$, $fc_{\$}$); the latter subsume information contained in various interest rate spreads and measures of uncertainty/risk and are plotted in Figure 1, where shaded areas correspond to periods of recession or financial crisis.[3] As shown in the Figure, both indicators track very accurately the phases of the business and financial cycle in the EA ($fc_{€}$) and the US ($fc_{\$}$). In particular, $fc_{\$}$ almost overlaps with both the adjusted ($ANFCI$) and not adjusted ($NFCI$) Chicago Fed US Net Financial Condition Index, yielding similar signals concerning rising and fading economic and financial distress over time. See Appendix A1 for full details about the dataset and computation of the financial indexes.

3.1 Model specification, estimation and forecasting

Consider the following autoregressive distributed lag model (AR-MF) for the nominal $US\$/€$ exchange rate log-return $\Delta e_{\$/€}$

$$\Delta e_{\$/€,t} = \theta_0 + \sum_{j=1}^{p} \theta_j \Delta e_{\$/€,t} + \sum_{i=1}^{q} \mathbf{y}'_{2,t-i} \boldsymbol{\gamma}_i + \varepsilon_t \tag{7}$$

where $\mathbf{y}_{2t}$ is the $N-1$ column vector of time t observations on the conditioning regressors, i.e., $\mathbf{y}_{2t} = \begin{bmatrix} g_{I,€\text{-}\$_t} & g_{€\text{-}\$_t} & ... & fc_{\$_t} \end{bmatrix}'$, θ_j, $j = 0, ..., p$, are parameters, $\boldsymbol{\gamma}_i$, $i = 0, ..., q$, are $N-1$ column vectors of parameters, and ε_t is a zero mean $i.i.d.$ process. In order to gauge the relevance of macro-financial information for the determination of the $US\$/€$ exchange rate, the AR-MF model in (7) has also been contrasted with the nested autoregressive (AR) model

$$\Delta e_{\$/€_t} = \theta_0 + \sum_{j=1}^{p} \theta_j \Delta e_{\$/€_{t-j}} + \varepsilon_t \tag{8}$$

[3] Concerning recessions, we follow the NBER chronology for the US and the OECD chronology for the EA. Hence, for the early 2000s recession: 4/2000 (start) - 11/2000 (end) for the US and 2/2001 - 7/2003 for the EA. For the late 2000s (Great) recession: 1/2008 - 6/2009 for the US and 3/2008 - 6/2009 for the EA. For the early 2010s recession: 7/2011 - 2/2013 for the EA. Concerning financial crises, for the dot-com bubble: 4/2000 (start) - 3/2003 (end). For the subprime financial crises: 8/2007 - 6/2009. For the EA sovereign debt crisis: 3/2010 - 3/2012.

obtained from (7) by setting $\theta_j = 0$, $j = 0, ..., p$, i.e., by neglecting the macro-financial information contained in $\mathbf{y}_{2t}$.

By inverting the AR polynomial $\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - ... - \theta_p L^p$ in (7) and setting $L = 1$ and $\varepsilon_t = 0$, the solved static long-run solution

$$\Delta e_{\$/€_t} = \theta_0^* + \mathbf{y}_{2t}'\boldsymbol{\gamma}^* \tag{9}$$

is obtained, where $\theta_0^* = \theta_0/\theta(1)$, $\boldsymbol{\gamma}^* = \theta(1)^{-1}\boldsymbol{\gamma}(1)$ is the $N-1$ column vector of long-run multipliers, and the generic sth element in the $N-1$ column vector $\boldsymbol{\gamma}(1)$ is $\boldsymbol{\gamma}_s(1) = \sum_{i=1}^{q} \gamma_{s,i}$, $s = 1, ..., N-1$. Long-run multipliers then yield information on the long-term effects of macroeconomic and financial fundamentals on US\$/€ exchange rate fluctuations.

A general to specific econometric modeling approach is implemented for model selection. In addition to standard goodness of fit measures and misspecification tests, a thorough assessment of forecasting accuracy of the selected model is also carried out. In particular, three sub samples are considered. The first estimation sample corresponds to the pre-crisis period 1999:1 through 2007:7 and embeds the dot-com bubble and the early 2000s recession as main episodes of financial and economic distress. The corresponding forecasting period is 2007:8 through 2009:6, i.e., from the beginning of the subprime mortgage financial crisis to the end of the ensuing (Great) recession. As shown in Figure 2, the $US\$/€$ kept appreciating during the early phase of the subprime financial crisis, eventually depreciating as the recession in the euro area deepened (2008:8-2009:2); a new phase of appreciation then started in 2009:3, few months before the end of the Great Recession (2009:6). The second estimation sample spans from 1999:1 through 2010:2 and, therefore, embeds, in addition to the early 2000s episodes, also the subprime financial crisis and ensuing Great recession. The corresponding forecasting sample is 2010:3 through 2013:2, i.e., from the beginning of the EA sovereign debt crisis through the end of the associated EA recession. As shown in Figure 3, the $US\$/€$ mostly depreciated over the latter period. Finally, the third estimation sample is 1999:1 through 2013:2 and, therefore, embed the early and late 2000s episodes, as well as the sovereign debt crisis and ensuing recession. The corresponding forecasting period is 2013:3 through 2015:6, a period of persisting uncertainty and economic and financial distress for the EA. As shown in Figure 4, over the third sub period, two main regimes can be singled out, i.e., an appreciation phase started few months before the end of the recession and persisting through March 2014; a successive depreciation phase, consistent with the weak and scattered recovery from the recession which led the ECB to deepen its expansionary monetary policy to eventually implement QE since January 2015.

3.1.1 Estimation results

Table 1 reports OLS estimates for the AR and AR-MF models, while Table 2 contains the solved static long-run solution for the AR-MF models. As shown in Table 1, Panel B, AR-MF models, independently of the sub sample investigated, are always well specified and show a remarkable in-sample predictive ability, as the unadjusted and adjusted coefficients of determination are in the range 0.65-0.79 and 0.57-0.73, respectively. Predictability of the $US\$/€$ appears to have deteriorated since the subprime financial crisis, as in the pre-crisis period (until 2007:7) about 80% of $US\$/€$ return variance is accounted by the AR-MF model, while a 20% reduction in the coefficient of determination can be noted (65%) as the sample is further extended over time. On the other hand, despite well specified according to standard misspecification tests, possibly with the exception of the second sub sample, the selected AR models show a very poor explanatory power (the coefficient of determination is in the range 0.10-0.17 across samples; Table 1, Panel B).

Some noteworthy features are also revealed by the comparison of AR-MF models across sub samples. For instance, as the estimation sample is expanded to include the two financial crises the selected specification becomes less parsimonious. Similarities across models concerning the type of macroeconomic predictors and their lag structure can also be noted, particularly for the pre-crisis and sovereign debt crisis estimation samples.

Moreover, while macro-financial variables significantly contribute also to the long-term determination of the $US\$/€$ exchange rate, the response of the currency to the various fundamentals is not stable across samples.[4] For instance, as shown in Table 2, with reference to the effects of external imbalances, an improvement in the EA current account leads to an appreciation of the $US\$/€$ for the pre-crisis estimation period only, consistent with the reduction in the risk premium associated with the consequential improvement in the net foreign asset position. An improvement in the US current account also leads to an appreciation of the $US\$/€$ for the pre-crisis and subprime financial crisis estimation samples; the sign of the linkage then reverses once the estimation sample also covers the sovereign debt crisis. Overall, the latter findings are consistent with the persistent worsening in the US trade balance over the pre-subprime crisis sample and the concurrent initial depreciation of the $US\$/€$ exchange rate lasting over two years (1999-2001), then occurring again in the mid-2000s (2005-2006); the large contraction in international trade scored during the Great Recession and concurrent improvement in the US trade balance and depreciation of the $US\$/€$ exchange rate then account for the inversion in sign detected once the sample is further extended over time (see Figure A3 in the Appendix).

Concerning the effects of changes in the monetary policy stance, consistent with the basic prediction of the monetary model, an increase in the real money growth differential leads to a depreciation of the $US\$/€$ for the pre-crisis period, as well as when the estimation period covers both financial crises. On the other hand, when only the subprime financial crisis is included in the estimation sample, the monetary policy stance is better reflected by the Libor rate differential; an increase in the latter variable then leads to a depreciation of the $US\$/€$, consistent with UIP. The latter finding is not surprising, given the much more expansionary monetary stance pursued by the Fed during the Great Recession than the ECB, yet the concurrent persistent depreciation in the US$/€. Indeed, the correlation between the money growth differential and the US$/€ return turns even positive over the period 2008 through 2013, then reversing again to negative values since 2014 (see Figure A3 in the Appendix).

Changes in the real and nominal side of the economy are also reflected in changes in the $US\$/€$. For instance, for the pre-crisis and the whole estimation samples, an increase in the unemployment rate differential leads to an appreciation of the $US\$/€$, likewise a reduction in industrial production and GDP growth rate differentials, or an increase in the inflation rate differential. The latter evidence, despite non consistent with the standard monetary model, is however coherent with prevailing relative economic conditions in the EA and US over the pre-crisis period, as the US was growing at a much faster pace than the EA, and yet the $US\$/€$ was steadily appreciating in 2002 through 2005 and then again since 2007 throughout the setting in of the Great Recession. As the estimation

[4] To facilitate the intepretation of the results, in Figure A3 in the Appendix we plot selected MA(12) smoothed macroeconomic and financial variables contrasted with similarly averaged $US\$/€$ exchange rate returns.

sample is then extended to include the subprime financial crisis, only inflation rate and industrial production growth differentials are still significant; moreover, for the latter variable a reversal in the sign of the multiplier can be noted, consistent with the positive correlation between the industrial production growth differential and the $US\$/€$ return which can be noted during the Great Recession (see Figure A3 in the Appendix).

Concerning the effects of commodity prices, an increase in the oil price leads to a long-term depreciation of the $US\$/€$, while the opposite holds for non-energy commodity and gold prices. In all cases, the latter linkages are only detected once the estimation sample is extended to include episodes of financial distress, i.e., they are not detected for the pre-crisis period. In terms of economic mechanics, patterns are consistent with the higher dependence of EA countries on oil imports than the US, an increase in the oil price therefore negatively affecting more the EA than the US, with consequential depreciation of the $US\$/€$. On the other hand, the positive correlation between the $US\$/€$ and non-energy commodity prices would point to a partial off-setting of non-energy commodity price shocks through changes in the value of the $US\$/€$ exchange rate.

Consistent with Bagliano and Morana (2015), risk factors and financial condition indexes are significant predictors once censoring according to sign is applied. In particular, value, momentum and the EA financial condition index are useful predictors for all the sub samples, while some instability is detected for the other risk factors. More specifically, for the pre-crisis period, an improvement in EA (US) financial conditions leads to an appreciation (depreciation) of the $US\$/€$ exchange rate; a consistent response of the $US\$/€$ to improved financial conditions in the EA is also found when the sample is extended to include both the subprime and sovereign debt crises. Finally, concerning the response of the $US\$/€$ to risk factor innovations, favorable revisions in expectations, as measured by an increase in the value and market factors, lead to an appreciation of the $US\$/€$; symmetrically, a worsening in the expected economic outlook, as measured by a decrease in the value factor, leads to its depreciation over the pre-crisis period. As the estimation sample is extended to include the subprime and sovereign debt crises, only the response to positive innovations is however statistically significant. Adverse revisions in expectations, as measured by an increase in momentum and a decrease in the profit factor, trigger a depreciation in the $US\$/€$ for the pre-crisis period; coherently, when the estimation sample is extended to include the subprime financial crisis, a decrease in momentum and in the profit factor causes an appreciation and a depreciation in the $US\$/€$, respectively; on the other hand, no significant effects can be found when the sample is further extended to include also the sovereign debt crisis. For the latter sample, the size and investment factors appear to show some signalling properties; yet, somewhat puzzling, changes in both directions in the latter variables are associated with an appreciation of the US$ in the long-term.

3.1.2 Forecasting the $US\$/€$ over crisis and post-crisis periods

As shown in Table 3, the results of the forecasting analysis are fairly consistent across samples and clear-cut. For instance, the remarkable in-sample predictive ability of the AR-MF models is surely not due to overfitting. In fact, relatively to AR models, AR-MF models yield, on average, a 30% reduction in the $RMSFE$ (28%, 22% and 35%, for the first, second and third subsample, respectively; Table 3, Panel A). Moreover, an over threefold increase in the correlation between actual and forecasted values is yield by AR-MF relatively to AR models (0.7, on average; 0.73 for the first and third sample; 0.68

for the second sample; 0.2 for AR models). Consistent with in-sample analysis results, also the out-of-sample performance of the AR-MF models is relatively weaker for the sovereign debt crisis forecasting sample.

According to estimated forecast combination regression (Table 3; Panel C), where the actual value of the $US\$/€$ exchange rate return is regressed on the forecasts generated by both models plus a constant, the gain in forecasting accuracy yield by AR-MF over AR models is also statistically significant. The estimated weight for the AR-2 model is in fact not statistically significant for the first and second forecasting horizon, and actually even negative for the third sample; on the other hand, the weight for the AR-MF model is always positive and strongly significant.

Moreover, by using BIC to compare forecast combination regressions (Table 3, Panel C) and Mincer-Zarnowitz regressions for the AR-MF models (Table 3; Panel B), it can be concluded that, apart from the third sample, combining forecasts from AR-MF and AR models is suboptimal to the use of forecasts generated by AR-MF models only. Yet, as already noted, for the post-EA subsample, forecasts generated by the AR model would enter with a negative, rather than the expected positive sign.

Finally, while both models generate unbiased forecasts, the point estimate of the slope parameter in the corresponding Mincer-Zarnowitz regressions is virtually equal to the optimal unity value and statistically significant for the AR-MF models only; on the other hand, for the AR models the slope parameter is only 0.6, and not statistically different from zero. Coherently, as shown in Figures 2-4, AR-MF models yield forecasts which track much more closely actual $US\$/€$ exchange rate returns and levels than AR models. While the AR-MF model fails to predict the depth of the $US\$/€$ depreciation ensued from the subprime financial crisis and associated (Great) recession, it however fails at a much lower extent than the AR model (Figure 2); similarly for the swift oscillations during the depreciation phase in 2011 and the appreciation phase in 2013 (Figure 3); moreover, only the AR-MF model is able to accurately track the depreciation phase of the $US\$/€$ started in 2014 and the eventual correction near end of sample (since May 2015; Figure 4).

4 US$/€-risk factor interactions in second moments

In order to further assess the interlinkage between the US$/€ exchange rate and risk factor innovations, second moment interactions are investigated by means of the semiparametric dynamic conditional correlation model (SP-DCC) of Morana (2015).

4.1 The SP-DCC model

The SP-DCC model is defined by following equations

$$\mathbf{y}_t = \boldsymbol{\mu}_t(\boldsymbol{\delta}) + \boldsymbol{\varepsilon}_t \tag{10}$$

$$\boldsymbol{\varepsilon}_t = \mathbf{H}_t^{1/2}(\boldsymbol{\delta})\mathbf{z}_t \tag{11}$$

where $\mathbf{y}_t$ is the $N \times 1$ column vector of the variables of interest, composed of the nominal exchange rate log-return $\Delta e_{\$/€}$ and the return on the five Fama-French factors $smb_\$$, $hml_\$$, $rmw_\$$, $cma_\$$, $mkt_\$$, plus Charart momentum $mom_\$$, i.e., $\mathbf{y}_t = \left[\begin{array}{cccc} \Delta e_{\$/€_t} & smb_{\$_t} & \ldots & mom_{\$_t} \end{array}\right]'$ with $N = 7$, $\boldsymbol{\mu}_t(\boldsymbol{\delta})$ is the $N \times 1$ conditional mean vector $E\left(\mathbf{y}_t|I_{t-1}\right)$, $\boldsymbol{\delta}$ is a vector of parameter, I_{t-1} is the sigma field; $\mathbf{H}_t(\boldsymbol{\delta})$ is the $N \times N$ conditional covariance matrix

$Var(\mathbf{y}_t|I_{t-1})$. Moreover, the random vector $\mathbf{z}_t$ is of dimension $N \times 1$ and assumed to be *i.i.d.* with first two moments $E(\mathbf{z}_t) = \mathbf{0}$ and $Var(\mathbf{z}_t) = \mathbf{I}_N$. Concerning the specification of the conditional covariance matrix $\mathbf{H}_t(\boldsymbol{\delta})$, we assume that the elements along its main diagonal, i.e., the conditional variances $Var(y_{i,t}|I_{t-1}) \equiv h_{ii,t}$ follow a GARCH(1,1) process

$$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \qquad i = 1, ..., N \tag{12}$$

subject to the usual restrictions to ensure that the conditional variances are positive almost surely at any point in time.

Concerning the definition of the conditional covariances, a nonparametric specification is posited, grounded on the identity

$$Cov(A, B) \equiv \frac{1}{4}\left[Var(A + B) - Var(A - B)\right] \tag{13}$$

given that $Var(A \pm B) = Var(A) + Var(B) \pm 2Cov(A, B)$.

Accordingly, the off-diagonal elements of $\mathbf{H}_t$, $Cov(y_{i,t}, y_{j,t}|I_{t-1}) \equiv h_{ij,t}$, are

$$h_{ij,t} = \frac{1}{4}\left[Var_{t-1}(y_{i,t} + y_{j,t}) - Var_{t-1}(y_{i,t} - y_{j,t})\right] \qquad i, j = 1, ..., N \qquad i \neq j. \tag{14}$$

By defining the transformed variables $y_{i,j,t}^+ \equiv y_{i,t} + y_{j,t}$ and $y_{i,j,t}^- \equiv y_{i,t} - y_{j,t}$, and assuming a GARCH(1,1) specification for their conditional variance processes $Var_{t-1}(y_{i,j,t}^+|I_{t-1}) \equiv h_{ij,t}^+$ and $Var_{t-1}(y_{i,j,t}^-|I_{t-1}) \equiv h_{ij,t}^-$ as well, we then have

$$h_{ij,t}^+ = \omega_{i,j}^+ + \alpha_{i,j}^+ \varepsilon_{i,j,t-1}^{+2} + \beta_{i,j}^- h_{i,t-1}^+ \qquad i, j = 1, ..., N \qquad i \neq j \tag{15}$$

$$h_{ij,t}^- = \omega_{i,j}^- + \alpha_{i,j}^- \varepsilon_{i,j,t-1}^{-2} + \beta_{i,j}^- h_{i,t-1}^- \qquad i, j = 1, ..., N \qquad i \neq j. \tag{16}$$

4.1.1 QML estimation of the SP-DCC model

Consistent and asymptotically normal estimation of the SP-DCC model is performed in two steps. Firstly, the conditional variances $h_{i,t}$, $i = 1, ..., N$, i.e., the elements along the main diagonal of $\mathbf{H}_t$, and $h_{ij,t}^+$, $h_{ij,t}^-$, $i, j = 1, ..., N$, $i \neq j$, are estimated equation by equation by means of QML, using conditional mean residuals; this yields $\hat{h}_{i,t}$, $i = 1, ..., N$, and $\hat{h}_{ij,t}^+$, $\hat{h}_{ij,t}^-$, $i, j = 1, ..., N$, $i \neq j$. Then, in the second step the off-diagonal elements of $\mathbf{H}_t$, $h_{ij,t}$, $i, j = 1, ..., N$, $i \neq j$, are estimated nonparametrically by computing

$$\hat{h}_{i,j,t} = \frac{1}{4}\left[\hat{h}_{i,j,t}^+ - \hat{h}_{i,j,t}^-\right] \qquad i, j = 1, ..., N \qquad i \neq j. \tag{17}$$

By further defining

$$\hat{D}_t = diag\left(\hat{h}_{1,t}^{1/2}, ..., \hat{h}_{N,t}^{1/2}\right)$$

the conditional correlation matrix R_t is then estimated as

$$\hat{R}_t = \hat{D}_t^{-1}\hat{H}_t\hat{D}_t^{-1}.$$

In order to ensure well behaved conditional covariance and correlation matrices, an ex-post correction is finally implemented (See Appendix A.4).

4.2 Empirical results

As described in the methodological section, the estimation of the SP-DCC model is performed using conditional mean residuals. Concerning the $US\$/€$, the latter are computed from the AR-MF specification employed to forecast over the post-EA sovereign crisis recession period, which is then estimated over the whole sample 1999:1 through 2015:6. As shown in Table 4, a GARCH(1,1) specification is required for the $US\$/€$ AR-MF model residuals to actually show white noise properties. In fact, the residuals from the conditionally homoskedastic version of the AR-MF model are still affected by autoregressive conditional heteroskedasticity. Possibly due to observational noise, the latter property is not detected by means of standard misspecification tests (Table 4; Panel B). It is however detected when observational noise is explicitly accounted for by fitting a stochastic volatility model for the log-absolute AR-MF residuals. As shown in the Table, the latter residuals do contain a sizable predictable component, as the estimated unobserved autoregressive component has persistence parameter ρ equal to 0.4 and variance σ_ρ^2 equal to 0.2, while the inverse signal to noise ratio σ_u^2/σ_ρ^2 is about 5. Evidence of predictable nonlinearity is also detected by the BDS test, rejecting the null hypothesis of independent and identical distribution ($i.i.d.$), at various embedding dimensions, for the AR-MF residuals. Coherently, both features are not any longer detected when AR-MF-GARCH(1,1) standardized residuals are assessed (Table 4; Panel B).

On the other hand, concerning risk factor innovations, a restricted VAR structure is employed, with own-variable lag length selected according to information criteria and specification tests. As we do not find evidence of serial correlation in risk factors, their residuals are simply computed as the demeaned original variables. A GARCH(1,1) specification has also been selected for all risk factor conditional variances, as well as for each of the 21 $N \times (N-1)/2$ distinct composite processes $h_{ij,t}^{+}$ and $h_{ij,t}^{-}$; in all cases the estimated parameters are well behaved, i.e., the sufficient condition for non-negative conditional variance at each point in time is respected and the persistence parameter, i.e., the sum of parameters for the lagged squared innovation and the lagged conditional variance are strictly below the threshold unitary value; moreover, standardized residuals are consistent with white noise properties.[5]

Finally, by comparing the original and (ex-post) transformed conditional correlations[6], we find that the average Theil's U index, across the sample of 21 conditional correlation processes, is just 0.09, with standard deviation equal to 0.07 (not reported). This means that the original and transformed (well-behaved) correlation processes are very close, i.e., the transformation required to make well-behaved the sequence of conditional correlation matrices leaves largely unchanged their original values, consistent with accurate estimation of second moments delivered by the SP-DCC model.

[5] For reasons of space, we do not report details for each of the corresponding 42 GARCH(1,1) models estimated for the composite variables. Yet we provide a summary of the findings in the Appendix, while a full set of results is available upon request from the author. Estimation results for risk factor conditional variances are also reported in the Appendix.

[6] The parameter in the sign preserving transformation k was set equal to 8, as resulting from the solution of the minimization problem presented in Appendix A.4. The estimated average positive eigenvalues used for nonlinear shrinkage are 0.0976, 0.2269, 0.4338, 0.7317, 1.0795, 1.6005 and 3.1718. Further details are available upon request from the author.

4.2.1 Conditional correlations and business cycle signals

In Figure 5 we plot the estimated conditional correlations relating the US$/€ return $e_{US\$/€}$ with each of the six risk factors, i.e., $mkt_{\$}$, $smb_{\$}$, $hml_{\$}$, $rmw_{\$}$, $cma_{\$}$ and $mom_{\$}$. The latter are denoted as CCM, CCS, CCH, CCR, CCC and CCW, respectively. Shaded areas correspond to periods of economic recession for the US and/or the EA economy. A plot contrasting conditional correlation dynamics with periods of financial crises is reported in the Appendix.

As shown in the Figure, all the estimated correlations are sizable, albeit weaker for CCS and CCH. Moreover, correlations tend to be sensitive to the state of the business and financial cycle. In fact, despite CCM, CCS and CCH (CCR and CCC) being mostly positive (negative) over the sample investigated, the latter tend to become negative (CCM) or more negative (CCR, CCC) during crisis periods, and, conversely, positive or less negative during non-crisis periods. Moreover, the state dependence of CCW is even a more clear-cut finding, as CCW is in general negative during crises and positive in non-crisis periods. As shown by Morana (2014b), a positive momentum innovation might signal a worsening in the expected economic outlook. The rationale is that if firms with stronger fundamentals outperform firms with weaker fundamentals during economic downturns, and if fundamentals are persistent and reflected in stock returns, positive momentum should be observed during recessions. The negative correlation with the $US\$/€$ exchange rate is then fully consistent with the € depreciating relatively to the US$ during crisis periods, as actually empirically observed.

In Figure 6 we then plot CCW, with its 95% confidence interval, over the period 2007-6 through 2015:6 (upper plot), as well as the $US\$/€$ exchange rate over the same period (bottom plot). For comparison we also report the Economic Sentiment Indicator (ESI) computed by the European Commission.[7] The comovement of CCW with the $US\$/€$ during recession periods is striking, the $US\$/€$ depreciating over most of the sovereign debt crisis and ensuing recession and CCW weakening progressively down to negative values, to eventually revert toward positive values as the $US\$/€$ exchange rate started appreciating again, leading the end of the (most recent) EA recession. The comovement of CCW with ESI through late 2013 is also striking. However, for the most recent period, different signals are yield by the two indicators.

In fact, as shown in Figure 6 (top plot), while ESI signals improving business cycle conditions, then stabilizing since early 2014, CCW has mostly fluctuated about a zero value since the end of the EA recession in 2013 and through early 2014. Yet, since June 2014, a significant and persistent reversion toward negative values can be observed, concurrent with the sizable depreciation in the $US\$/€$. As actual figures show, rather than recovery, scattered and sluggish GDP growth, as well as stagnating credit supply well describe EA macroeconomic conditions over the recent post-recession period. The latter actually forced the ECB to deepen its expansionary monetary policy stance by cutting the main refinancing rate down to +0.15% in June 2014 and then to +0.05% in September 2014, eventually followed by the introduction of QE in January 2015. The negative values of CCW over 2015 are also consistent with the raising uncertainty concerning the survival of the EA itself, fueled by persistent solvency problems in Greece, newly exploded in late spring/early summer 2015. The discrepancy between CCW and ESI over the most recent sample is then clear-cut evidence of the value added and excess information contained in CCW.

[7] Available at http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm.

5 Conclusions

In this paper we investigate the determinants of the US$/€ exchange rate since its introduction in 1999, with particular reference to the recent financial crises. Specifically, we estimate a reduced form econometric model for both the conditional mean and variance of the $US\$/€$ exchange rate return, conditioning on a large set of macroeconomic and financial variables, and use it to forecast over three separate time spans, covering the subprime financial crisis, the sovereign debt crisis, and the post-sovereign debt crisis period through 2015:6, respectively. Surprisingly, little is known about the determinants of the $US\$/€$ exchange rate return during the recent financial crises, as most studies do not consider data beyond 2010.

The econometric model is grounded on the asset pricing theory of exchange rate determination, which posits that the current exchange rate depends on the present discounted value of the future stream of fundamentals. In the latter framework, exchange rate fluctuations are then accounted by news or revisions in expectations about fundamentals. In this respect, we innovate the literature by including in the information set, in addition to standard macroeconomic fundamentals, financial condition indexes and direct measures of changing market expectations about the economic outlook, as yield by risk factors likewise the five Fama and French (1993, 2015) factors and Charart (1997) momentum.

We find that the estimated reduced form econometric models (AR-MF) are broadly in line with a hybrid version of the monetary model, where, in addition to monetary policy stance indicators, risk factor information and (new) measures of EA and US financial conditions sizably contribute to the determination of the $US\$/€$ exchange rate. Overall, the results show that the AR-MF models have remarkable in-sample predictive ability, accounting for 60% to 80% of $US\$/€$ returns variance, fivefold larger than for standard autoregressive models (AR) neglecting macro-financial information. AR($\cdot$)-MF models also yield an average 30% reduction in $RMSFE$ out-of-sample and are forecast encompassing, relatively to AR models.

Finally, by assessing interlinkages in second-moments, we uncover a stable relationship between the US$/€-Charart momentum conditional correlation (CCW) and the state of the global and EA economic cycle. In particular, the latter dynamic conditional correlation becomes negative during periods of recession and positive during phases of economic expansion. A progressive weakening in EA economic conditions is then detected since June 2014, in contrast with signals yield by available economic sentiment measures, likewise the Economic Sentiment Index published by the European Commission (ESI). As actual figures show, rather than recovery, scattered and sluggish GDP growth, as well as stagnating credit supply, well describe EA macroeconomic conditions over the recent post-recession period. The latter actually led the ECB to further deepen its expansionary stance and eventually to introduce QE in January 2015. The negative values of the proposed indicator over the last part of the sample are also consistent with raising uncertainty concerning the survival of the EA itself, fueled by persistent solvency problems in Greece, newly exploded in late spring/early summer 2015. The discrepancy with ESI since 2014 is then clear-cut evidence of the value added and the excess information of CCW, easily exploitable also within a system of early warning indicators of macroeconomic stress.

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Table 1: US$/€ exchange rate return determination: dynamic econometric models

Panel A: AR and AR-MF models: $\Delta e_{US\$/€,t}$								
Estimation sample: 1999:1-2007:7			**Estimation sample: 1999:1-2010:2**			**Estimation sample: 1999:1-2013:2**		
Variables	**AR(2)**	**AR(1)-MF**		**AR(2)**	**AR(2)-MF**		**AR(2)**	**AR(2)-MF**
$\Delta e_{US\$/€,\ t-1}$	-0.2291 (0.1087)	0.1425 (0.0665)	$\Delta e_{US\$/€,\ t-1}$	0.3839 (0.0914)	0.2752 (0.0721)	$\Delta e_{US\$/€,\ t-1}$	-0.1398 (0.0766)	0.3636 (0.0609)
$\Delta e_{US\$/€,\ t-2}$	0.4449 (0.1113)	-	$\Delta e_{US\$/€,\ t-2}$	-0.1497 (0.0914)	-0.1223 (0.0730)	$\Delta e_{US\$/€,\ t-2}$	0.3399 (0.0769)	-0.1515 (0.0620)
$u_{€-\$,t-11}$		2.2137 (0.9841)	$g_{I,€-\$,t-22}$		0.4642 (0.1778)	$u_{€-\$,t-6}$		-2.4706 (0.9749)
$em_{€-\$,t-5}$		-0.7495 (0.2068)	$\pi_{€-\$,t-12}$		1.1610 (0.3250)	$u_{€-\$,t-11}$		2.5172 (0.9916)
$\pi_{€-\$,t-12}$		1.2903 (0.3204)	$bp_{\$,t-17}$		0.1464 (0.0620)	$u_{€-\$,t-21}$		1.9263 (0.9283)
$\Delta g_{I,€-\$,t-18}$		-0.2351 (0.0841)	$o_{\$,t-23}$		-0.0474 (0.0236)	$em_{€-\$,t-5}$		-0.4594 (0.1738)
$\Delta g_{€-\$,t-16}$		-10.2266 (2.6670)	$c_{\$,t-14}$		0.2603 (0.0657)	$\pi_{€-\$,t-12}$		1.0536 (0.2743)
$bp_{\$,t-17}$		0.1885 (0.0521)	$li_{€-\$,t-1}$		3.6001 (0.8278)	$g_{I,€-\$,t-20}$		-0.6487 (0.1370)
$bp_{€,t-18}$		0.1402 (0.0430)	$li_{€-\$,t-2}$		-4.2908 (0.8420)	$\Delta g_{I,€-\$,t-1}$		-0.2516 (0.1063)
$fc^{-}_{\$,t-5}$		-1.0369 (0.2191)	$li_{€-\$,t-13}$		1.1776 (0.3969)	$\Delta g_{I,€-\$,t-2}$		-0.4230 (0.1062)
$fc^{-}_{€,t-15}$		2.3602 (0.7385)	$li_{€-\$,t-17}$		-0.6704 (0.3710)	$\Delta g_{I,€-\$,t-17}$		0.2266 (0.0876)
$hml^{-}_{\$,t-7}$		-0.5980 (0.1026)	$mom^{-}_{\$,t-10}$		0.0866 (0.0361)	$\Delta g_{I,€-\$,t-21}$		-0.2468 (0.0873)
$rmw^{-}_{\$,t-21}$		0.2243 (0.0500)	$rmw^{-}_{\$,t-6}$		-0.3439 (0.1222)	$\Delta g_{€-\$,t-16}$		-6.6420 (2.5380)
$mkt^{+}_{\$,t-7}$		-0.1480 (0.0626)	$rmw^{-}_{\$,t-12}$		0.3029 (0.1215)	$bp_{\$,t-15}$		-0.0797 (0.0466)
$mkt^{+}_{\$,t-14}$		0.2805 (0.0550)	$rmw^{-}_{\$,t-18}$		-0.3345 (0.0759)	$o_{\$,t-8}$		-0.0538 (0.0166)
$hml^{+}_{\$,t-16}$		0.1970 (0.0499)	$cma^{-}_{\$,t-11}$		0.5180 (0.1669)	$c_{\$,t-14}$		0.1763 (0.0488)
$mom^{+}_{\$,t-11}$		-0.1011 (0.0384)	$fc^{+}_{€,t-15}$		0.4661 (0.2071)	$gd_{\$,t-4}$		0.1199 (0.0358)
			$hml^{+}_{\$,t-7}$		-0.1614 (0.0700)	$fc^{-}_{€,t-5}$		1.4600 (0.3236)
			$hml^{+}_{\$,t-18}$		0.1678 (0.0683)	$smb^{-}_{\$,t-18}$		0.2525 (0.0789)
			$hml^{+}_{\$,t-24}$		0.1342 (0.0608)	$smb^{-}_{\$,t-19}$		0.1720 (0.0759)
						$cma^{-}_{\$,t-10}$		0.3258 (0.1506)
						$smb^{+}_{\$,t-22}$		0.1461 (0.0586)
						$hml^{+}_{\$,t-24}$		0.1618 (0.0558)
						$mom^{+}_{\$,t-1}$		0.1125 (0.0515)
						$mom^{+}_{\$,t-10}$		-0.1118 (0.0496)
						$cma^{+}_{\$,t-11}$		0.2095 (0.0857)
						$mkt^{+}_{\$,t-6}$		0.2170 (0.0525)

Panel B: Goodness of fit and misspecification tests								
Estimation sample: 1999:1-2007:7			**Estimation sample: 1999:1-2010:2**			**Estimation sample: 1999:1-2013:2**		
	AR(2)	**AR(1)-MF**		**AR(2)**	**AR(2)-MF**		**AR(2)**	**AR(2)-MF**
R^2	0.1774	0.7890	R^2	0.1370	0.6500	R^2	0.1064	0.6692
$\overline{R^2}$	0.1551	0.7327	$\overline{R^2}$	0.1206	0.5696	$\overline{R^2}$	0.0955	0.5923
BIC	4.3075	3.7395	BIC	4.5924	4.4282	BIC	4.6279	4.4644
$AR\ 1-5$	0.2769	0.9673	$AR\ 1-7$	0.6256	0.2835	$AR\ 1-7$	0.8534	0.3998
$ARCH\ 1-5$	0.8471	0.4218	$ARCH\ 1-7$	0.0030	0.6879	$ARCH\ 1-7$	0.0590	0.3252
BJ	0.3901	0.7648	BJ	0.0764	0.0695	BJ	0.4521	0.6555
$RESET23$	0.1849	0.6272	$RESET23$	0.0158	0.4901	$RESET23$	0.0718	0.9588

In the Table we report the estimated AR and AR-MF models for the three selected subsamples. Panel A reports the estimated parameters with standard errors in round brackets. Panel B reports the unadjusted and adjusted coefficient of determination (R^2 and $\overline{R^2}$), as well the p-value of standard misspecification tests, i.e., the LM Breusch-Godfrey serial correlation (AR) test, the Engle ARCH effects ($ARCH$) test, the Bera-Jarque normality test (BJ) and the Ramsey Reset functional form test for squares and cubes ($RESET23$). The regressors are the EA current account in changes ($bp_{€}$), the US trade balance in changes ($bp_{\$}$), the real excess money growth differential ($em_{€-\$}$), the unemployment rate differential in changes ($u_{€-\$}$), the rates of growth for industrial production ($g_{I,€-\$}$) and GDP ($g_{€-\$}$) differentials, also in changes ($\Delta g_{I,€-\$}$, $\Delta g_{€-\$}$), the oil price rate of growth ($o_{\$}$), the non-energy commodity price index rate of growth ($c_{\$}$), the gold price rate of growth ($gd_{\$}$), the inflation rate differential ($\pi_{€-\$}$); the remaining variables enters the equation according to an asymmetric specification based on sign, i.e., positive (+) and negative (-) values individually considered, i.e., the EA financial condition index ($fc_{€}$), the Fama-French US market ($mkt_{\$}$), size ($smb_{\$}$), value ($hml_{\$}$), profit ($rmw_{\$}$) and investment ($cma_{\$}$) factors, and Charart momentum ($mom_{\$}$).

Table 2: Solved static-long run solution for AR-MF models

Solved static long-run solution for AR-MF models: $\Delta e_{US\$/€,t}$					
Estimation sample: 1999:1-2007:7		Estimation sample: 1999:1-2010:2		Estimation sample: 1999:1-2013:2	
	AR(1)-MF		**AR(2)-MF**		**AR(2)-MF**
$u_{€-\$}$	2.5815 (1.1690)	$g_{I,€-\$}$	0.5479 (0.2236)	$u_{€-\$}$	2.5043 (1.8820)
$em_{€-\$}$	-0.8741 (0.2543)	$\pi_{€-\$}$	1.3704 (0.4142)	$em_{€-\$}$	-0.5832 (0.2280)
$\pi_{€-\$}$	1.5048 (0.4036)	$bp_{\$}$	0.1728 (0.0759)	$\pi_{€-\$}$	1.3373 (0.3620)
$\Delta g_{I,€-\$}$	-0.2741 (0.1018)	$o_{\$}$	-0.0559 (0.0303)	$g_{I,€-\$}$	-0.8235 (0.1959)
$\Delta g_{€-\$}$	-11.9262 (3.0200)	$c_{\$}$	0.3073 (0.0843)	$\Delta g_{I,€-\$}$	-0.8819 (0.3138)
$bp_{\$}$	0.2198 (0.0606)	$li_{€-\$}$	-0.2166 (0.2387)	$\Delta g_{€-\$}$	-8.4311 (3.2850)
$bp_{€}$	0.1635 (0.0491)	$mom_{\$}^{-}$	0.1022 (0.0429)	$bp_{\$}$	-0.1011 (0.0590)
$fc_{\$}^{-}$	-1.2092 (0.2604)	$rmw_{\$}^{-}$	-0.4433 (0.1856)	$o_{\$}$	-0.0682 (0.0208)
$fc_{€}^{-}$	2.7525 (0.8453)	$cma_{\$}^{-}$	0.6115 (0.2023)	$c_{\$}$	0.2238 (0.0671)
$hml_{\$}^{-}$	-0.6973 (0.1250)	$fc_{€}^{+}$	0.5502 (0.2571)	$gd_{\$}$	0.1522 (0.0469)
$rmw_{\$}^{-}$	0.2615 (0.0612)	$hml_{\$}^{+}$	0.1660 (0.1100)	$fc_{€}^{-}$	1.8532 (0.4323)
$mkt_{\$}^{+}$	0.1545 (0.0873)			$smb_{\$}^{-}$	0.5388 (0.1535)
$hml_{\$}^{+}$	0.2297 (0.0599)			$cma_{\$}^{-}$	0.4136 (0.1995)
$mom_{\$}^{+}$	-0.1179 (0.0462)			$smb_{\$}^{+}$	0.1854 (0.0784)
				$hml_{\$}^{+}$	0.2053 (0.0695)
				$mom_{\$}^{+}$	0.0008 (0.0866)
				$cma_{\$}^{+}$	0.2659 (0.1085)
				$mkt_{\$}^{+}$	0.2755 (0.0726)

In the Table we report the estimated parameters for the solved static long-run solution for the selected AR-MF models. Standard errors are reported in round brackets. The regressors are the EA current account in changes ($bp_{€}$), the US trade balance in changes ($bp_{\$}$), the real excess money growth differential ($em_{€-\$}$), the unemployment rate differential in changes ($u_{€-\$}$), the rates of growth for industrial production ($g_{I,€-\$}$) and GDP ($g_{€-\$}$) differentials, also in changes ($\Delta g_{I,€-\$}, \Delta g_{€-\$}$), the oil price rate of growth ($o_{\$}$), the non-energy commodity price index rate of growth ($c_{\$}$), the gold price rate of growth ($gd_{\$}$), the inflation rate differential ($\pi_{€-\$}$); the remaining variables enters the equation according to an asymmetric specification based on sign, i.e., positive (+) and negative (-) values individually considered, i.e., the EA financial condition index ($fc_{€}$), the Fama-French US market ($mkt_{\$}$), size ($smb_{\$}$), value ($hml_{\$}$), profit ($rmw_{\$}$) and investment ($cma_{\$}$) factors, and Charart momentum ($mom_{\$}$).

Table 3: Out of sample forecasting evaluation analysis

Panel A: RMSFE and correlation statistics						
	Forecasting sample: 2007:8-2009:6 Subprime mortgage crisis and GR		Forecasting sample: 2010:3-2013:2 EA sovereign crisis and recession		Forecasting sample: 2013:3-2015:6 Post EA sovereign crisis recession	
	AR(2)	AR(1)-MF	AR(2)	AR(2)-MF	AR(2)	AR(2)-MF
$\rho_{a,f}$	0.2758	0.7285	0.2759	0.6759	0.1442	0.7357
$RMSFE$	3.2003	2.3187	2.4359	1.8820	2.0653	1.3485
$RMSFE_{\frac{AR\text{-}X}{AR}}$	1	0.7245	1	0.7726	1	0.6530
Panel B: Mincer-Zarnowitz forecast regressions						
	Forecasting sample: 2007:8-2009:6 Subprime mortgage crisis and GR		Forecasting sample: 2010:3-2013:2 EA sovereign crisis and recession		Forecasting sample: 2013:3-2015:6 Post EA sovereign crisis recession	
	AR(2)	AR(1)-MF	AR(2)	AR(2)-MF	AR(2)	AR(2)-MF
R^2	0.0761	0.5309	0.0776	0.4568	0.0208	0.5413
BIC	5.4072	4.7297	4.8041	4.2746	4.4307	3.6723
γ_0	0.0554 (0.6885)	-0.5935 (0.5100)	-0.0466 (0.4151)	-0.2311 (0.3199)	-0.5672 (0.3921)	0.0400 (0.2897)
γ_1	0.6231 (0.4734)	1.0892 (0.2235)	0.7150 (0.4227)	0.9039 (0.1690)	0.4363 (0.5869)	1.0362 (0.1871)
Panel C: Forecast combination regression						
	Forecasting sample: 2007:8-2009:6 Subprime mortgage crisis and GR		Forecasting sample: 2010:3-2013:2 EA sovereign crisis and recession		Forecasting sample: 2013:3-2015:6 Post EA sovereign crisis recession	
R^2	0.5432		0.4593		0.6971	
BIC	4.8392		4.3695		3.3763	
θ_0	-0.5834 (0.5158)		-0.2225 (0.3247)		0.1408 (0.2417)	
θ_1	0.2586 (0.3507)		0.1365 (0.3497)		-1.5182 (0.4234)	
θ_2	1.0499 (0.2322)		0.8796 (0.1822)		1.4730 (0.1971)	

In the Table we report the results of the forecast evaluation analysis. Panel A reports the root mean square forecast error (RMSFE) and the relative RMSFE ($RMSFE_{\frac{AR\text{-}MF}{AR}}$), as well as the correlation coefficient between actual and forecasted values. Panel B reports the estimated parameters of the Mincer-Zarnowitz regressions $y_t^a = \lambda_0 + \lambda_1 y_t^f + \varepsilon_t$, where y_t^a and y_t^f are the actual and forecasted value, ε_t is white noise. Panel C reports the estimated parameter of the forecast encompassing regression $y_t^a = \theta_0 + \theta_1 y_t^{f_{AR}} + \theta_2 y_t^{f_{AR-MF}} + \varepsilon_t$, where y_t^a is the actual value, $y_t^{f_{AR}}$ and $y_t^{f_{AR-MF}}$ are the forecasted values generated by the AR and AR-MF models, respectively and ε_t is white noise. In both Panel B and C standard errors are reported in round brackets; also the coefficient of determination (R^2) and the BIC information criterion (BIC) are reported in both cases.

Table 4: US$/€ exchange rate return: full sample dynamic econometric model

Panel A: Reduced form whole sample regression: $\Delta e_{US\$/€,t}$									
Conditional mean								Conditional variance	
$\Delta e_{US\$/€,\, t-1}$	0.3295 (0.0559)	$g_{I,€-\$,t-20}$	-0.6654 (0.1193)	$o_{\$,t-8}$	-0.0550 (0.0144)	$smb^{+}_{\$,t-22}$	0.1460 (0.0505)	ω	0.2922 (0.2353)
$\Delta e_{US\$/€,\, t-2}$	-0.1135 (0.0655)	$\Delta g_{I,€-\$,t-1}$	-0.2697 (0.1089)	$c_{\$,t-14}$	0.1725 (0.0485)	$hml^{+}_{\$,t-24}$	0.1619 (0.0511)	ε^2_{t-1}	0.1185 (0.0698)
$u_{€-\$,t-6}$	-2.5257 (0.9796)	$\Delta g_{I,€-\$,t-2}$	-0.4434 (0.1178)	$gd_{\$,t-4}$	0.1325 (0.0340)	$mom^{+}_{\$,t-1}$	0.1219 (0.0511)	h_{t-1}	0.7385 (0.1330)
$u_{€-\$,t-11}$	-2.6080 (0.8847)	$\Delta g_{I,€-\$,t-17}$	0.2518 (0.0725)	$fc^{-}_{€,t-5}$	1.4574 (0.2898)	$mom^{+}_{\$,t-10}$	-0.1197 (0.0408)		
$u_{€-\$,t-21}$	2.3867 (1.0502)	$\Delta g_{I,€-\$,t-21}$	-0.2480 (0.0818)	$smb^{-}_{\$,t-18}$	0.2484 (0.0595)	$cma^{+}_{\$,t-11}$	0.2202 (0.0655)	R^2	0.6647
$em_{€-\$,t-5}$	-0.4841 (0.1343)	$\Delta g_{€-\$,t-16}$	-6.6758 (2.0019)	$smb^{-}_{\$,t-19}$	0.1728 (0.0572)	$mkt^{+}_{\$,t-6}$	0.2068 (0.0536)	$\overline{R^2}$	0.6018
$\pi_{€-\$,t-12}$	1.0598 (0.1993)	$bp_{\$,t-15}$	-0.0925 (0.0379)	$cma^{-}_{\$,t-10}$	0.3251 (0.1251)				

Panel B: Misspecification tests			
Residuals: AR-MF		Standardized residuals: AR-MF-GARCH	
$AR\ 1-7$	0.2934	$Q(20)$	0.1467
		$Q_2(20)$	0.9521
$ARCH\ 1-7$	0.3363	$ARCH\ 1-7$	0.7766
BJ	0.7517	BJ	0.9744
$RESET23$	0.7683	$S\ \&\ B$	0.2163
$BDS(2)$	0.0060	$BDS(2)$	0.4420
$BDS(3)$	0.0033	$BDS(3)$	0.3266
$BDS(4)$	0.0119	$BDS(4)$	0.7065
$BDS(5)$	0.0383	$BDS(5)$	0.6821
$BDS(6)$	0.0101	$BDS(6)$	0.8662
Log-absolute residuals		Log-absolute standardized residuals	
σ^2_u	0.9336	σ^2_u	1.0872
σ^2_ϕ	0.1808	σ^2_ϕ	0.0217
ρ	0.3847	ρ	0.1665

In the Table, Panel A, we report whole sample estimates for the selected AR-MF-GARCH model, with (heteroscedasticity consistent) standard errors in round brackets, as well as the unadjusted and adjusted coefficient of determination (R^2 and $\overline{R^2}$). The regressors are the EA current account in changes ($bp_€$), the US trade balance in changes ($bp_\$$), the real excess money growth differential ($em_{€-\$}$), the unemployment rate differential in changes ($u_{€-\$}$), the rates of growth for industrial production ($g_{I,€-\$}$) and GDP ($g_{€-\$}$) differentials, also in changes ($\Delta g_{I,€-\$}, \Delta g_{€-\$}$), the oil price rate of growth ($o_\$$), the non-energy commodity price index rate of growth ($c_\$$), the gold price rate of growth ($gd_\$$), the inflation rate differential ($\pi_{€-\$}$); the remaining variables enters the equation according to an asymmetric specification based on sign, i.e., positive (+) and negative (-) values individually considered, the EA financial condition index ($fc_€$), the Fama-French US market ($mkt_\$$), size ($smb_\$$), value ($hml_\$$), profit ($rmw_\$$) and investment ($cma_\$$) factors, and Charart momentum ($mom_\$$). Finally, h_{t-1} is the lagged conditional variance, ε^2_{t-1} is the lagged squared conditional mean residual, ω is the intercept in the conditional variance equation. In Panel B we report the p-value of standard misspecification tests for the residuals of the AR-MF model, i.e., the LM Breusch-Godfrey serial correlation (AR) test, the Engle ARCH effects ($ARCH$) test, the Bera-Jarque normality test (BJ), the Ramsey Reset functional form test for squares and cubes ($RESET23$), and the Brock, Dechert and Scheinkman test for independent and identical distribution (i.i.d), for various embedding dimensions (2 to 6). Misspecification tests are also reported for standardized residuals of the AR-MF-GARCH model, i.e., the Box-Ljung test for serial correlation in standardized ($Q(20)$) and squared standardized ($Q_2(20)$) residuals up to the 20th order, the joint Engle-

Ng sign and size bias test ($S \& B$). In Panel B we also report the estimated stochastic volatility models $y_t = \phi_t + u_t$ using the log absolute residuals ($\left|\hat{\varepsilon}_t\right|$) and the log absolute standardized residuals ($\left|\hat{\varepsilon}_t / \hat{h}_t^{0.5}\right|$), where $y_t = \left|\hat{\varepsilon}_t\right|$, $\left|\hat{\varepsilon}_t / \hat{h}_t^{0.5}\right|$, $\phi_t = \rho\phi_{t-1} + v_{\phi,t}$, $v_{\phi,t} \sim NID(0,\sigma_\phi^2)$, $u_t \sim NID(0,\sigma_u^2)$. In particular, the estimated AR parameter (ρ) and the estimated variances σ_u^2 and σ_ϕ^2 are reported.

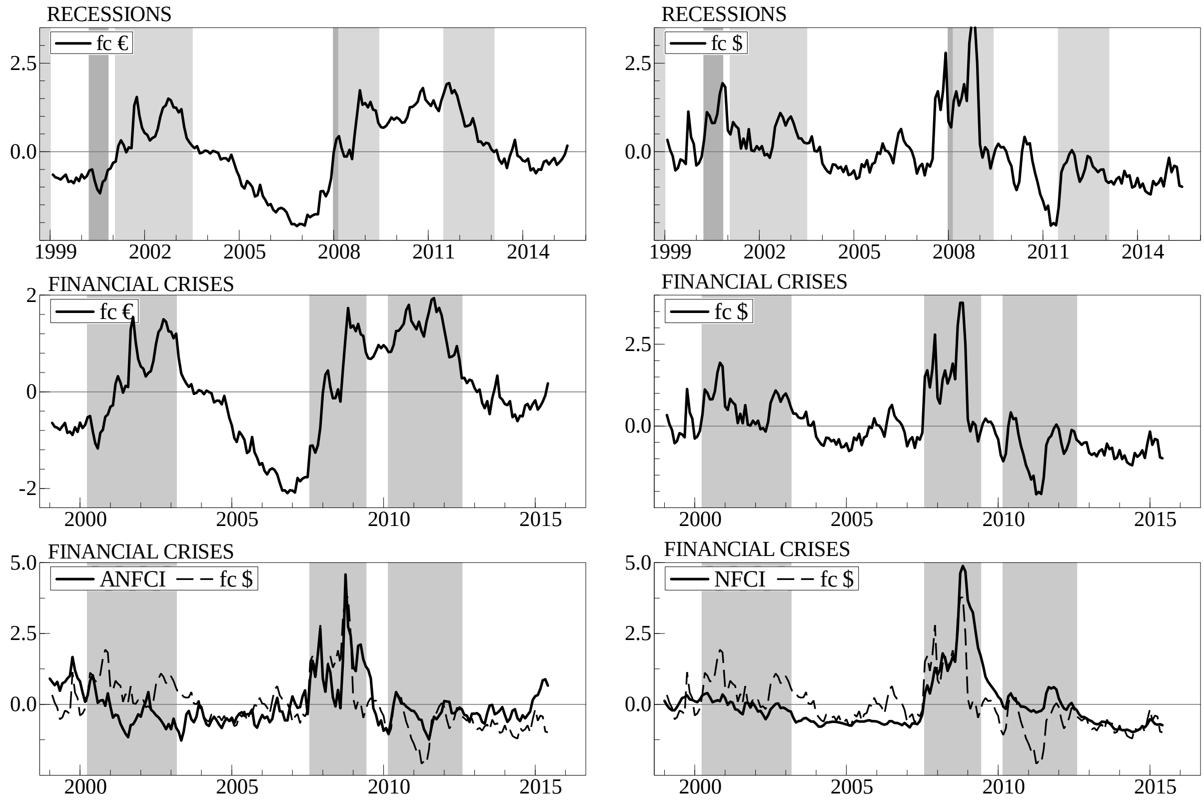

Figure 1: In the figure we plot the estimated EA ($fc_{€}$) and US ($fc_{\$}$) financial condition indexes. Shaded areas refer to recession periods (top plots) for the US (darker shade) and the EA (lighter shade); to financial crises periods (center and bottom plots) for the US and the EA. The US ($fc_{\$}$) financial condition index is also contrasted with the Chicago Fed Net Financial Condition Index (NGCI) and Adjusted Net Financial Condition Index (bottom plots). Concerning recessions, we follow the NBER chronology for the US and the OECD chronology for the EA. Hence, the timeline is as follows. For the early 2000s recession: April 2000 (start) and November 2000 (end) for the US; February 2001 (start) and July 2003 (end) for the EA. For the late 2000s (Great) recession: January 2008 (start) and June 2009 (end) for the US; March 2008 (start) and June 2009 (end) for the EA. For the early 2010s recession: July 2011 (start) and February 2013 (end) for the EA. Concerning the dating of financial crises, the selected timeline is as follows. For the dot-com bubble: April 2000 (start) and March 2003 (end), where we associate the beginning of the crisis with the burst of the stock market bubble, i.e., the beginning of the persistent decline in the S&P500 index which lasted through February 2003; the end of the financial cycle is then marked by the steady stock market recovery beginning in March 2003. For the subprime financial crises: August 2007 (start) and June 2009 (end), where we associate the beginning of the financial cycle with BNP-Paribas announcing its inability to price three of its investment funds based on US subprime mortgage loans and its end with the normalization of the short-end of the LIBOR-OIS swap rates term structure (i.e., with the normalization in interbank market conditions). See Cassola and Morana (2013) and Morana (2014) for supporting empirical evidence. Moreover, for the EA sovereign debt crisis we associate the beginning of the crisis to the announcement by EA finance ministers in March 2010 of having agreed on a mechanism to help Greece, and the European Commission President, José Manuel Barroso, urging EU member states to agree on a standby aid package for Greece. On the other hand, we mark the end of the crisis between March and August 2012, following the implementation of the Second bailout package for Greece in February 2012 and the ECB holding a second long term refinancing operation providing EA banks with further €529.5 billion in loans. This lead to a persistent normalization of the EA interbank market since March 2012, which was again under stress since early 2010.

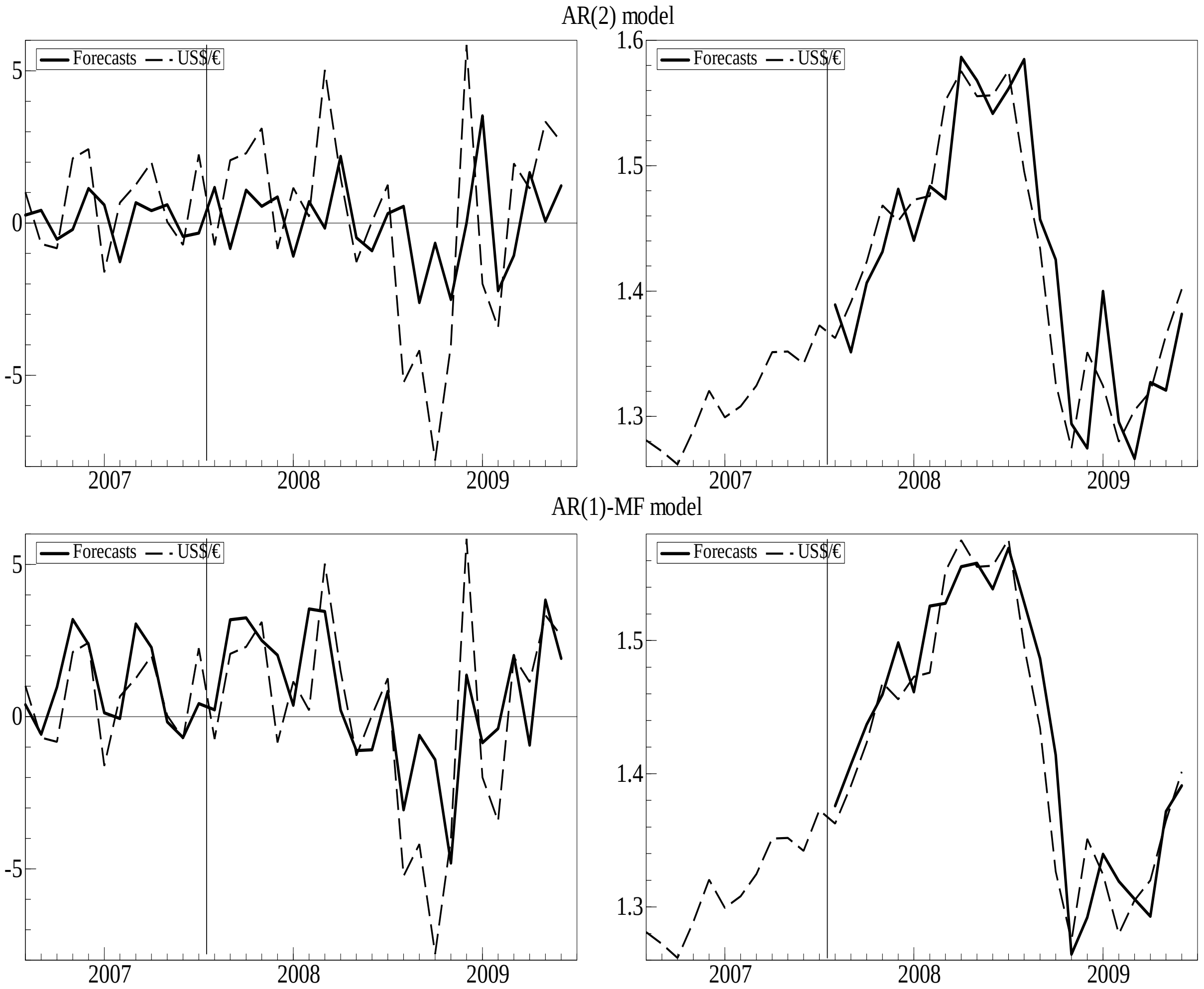

Figure 2: In the Figure 1-month ahead forecasts for both the US$/€ return (left hand side plots) and level (right hand side plots), over the subprime crisis period, generated by means of the selected AR (top panels) and AR-MF (bottom panels) models are contrasted.

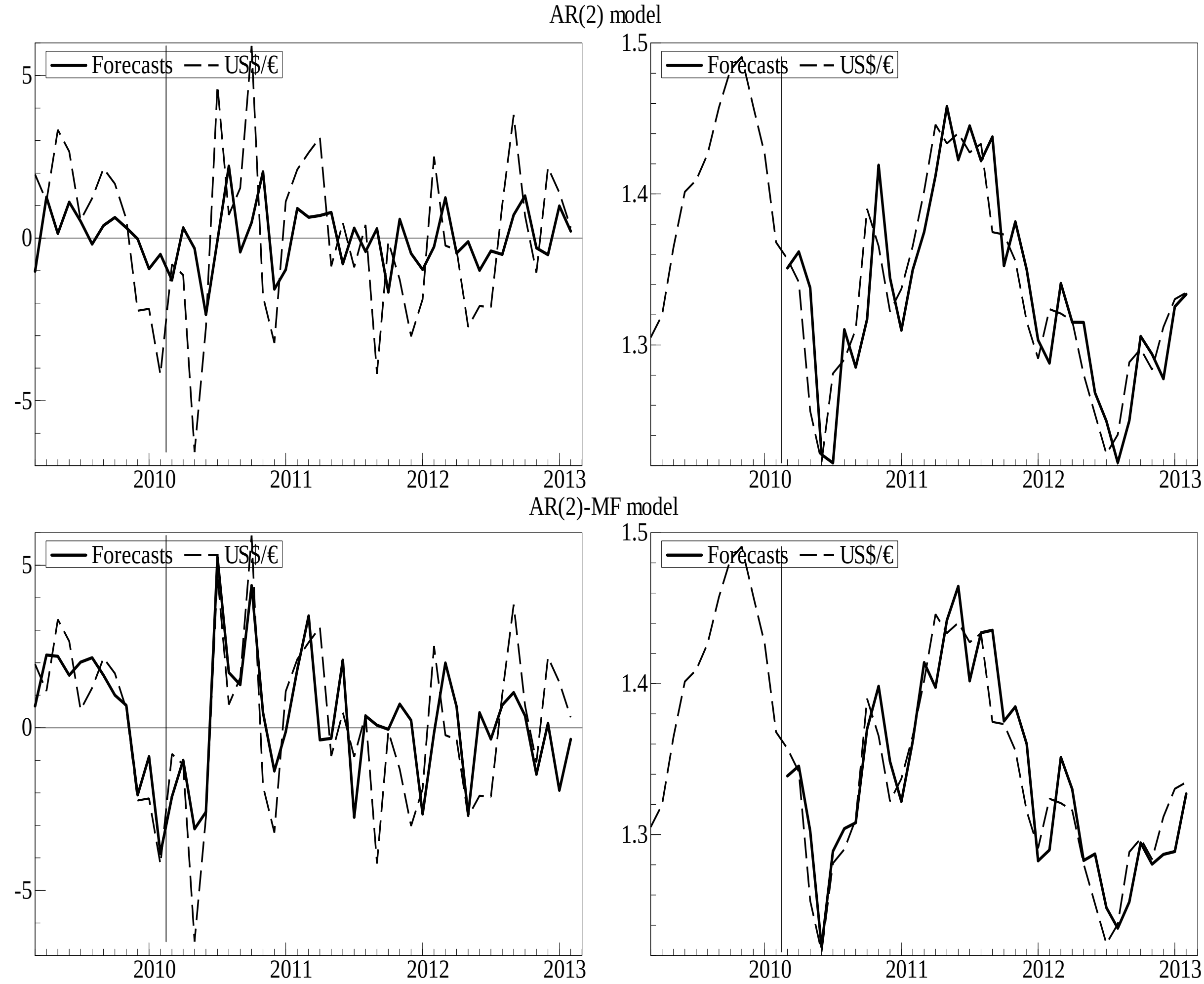

Figure 3: In the Figure 1-month ahead forecasts for both the US$/€ return (left hand side plots) and level (right hand side plots), over the sovereign debt crisis period, generated by means of the selected AR (top panels) and AR-MF (bottom panels) models are contrasted.

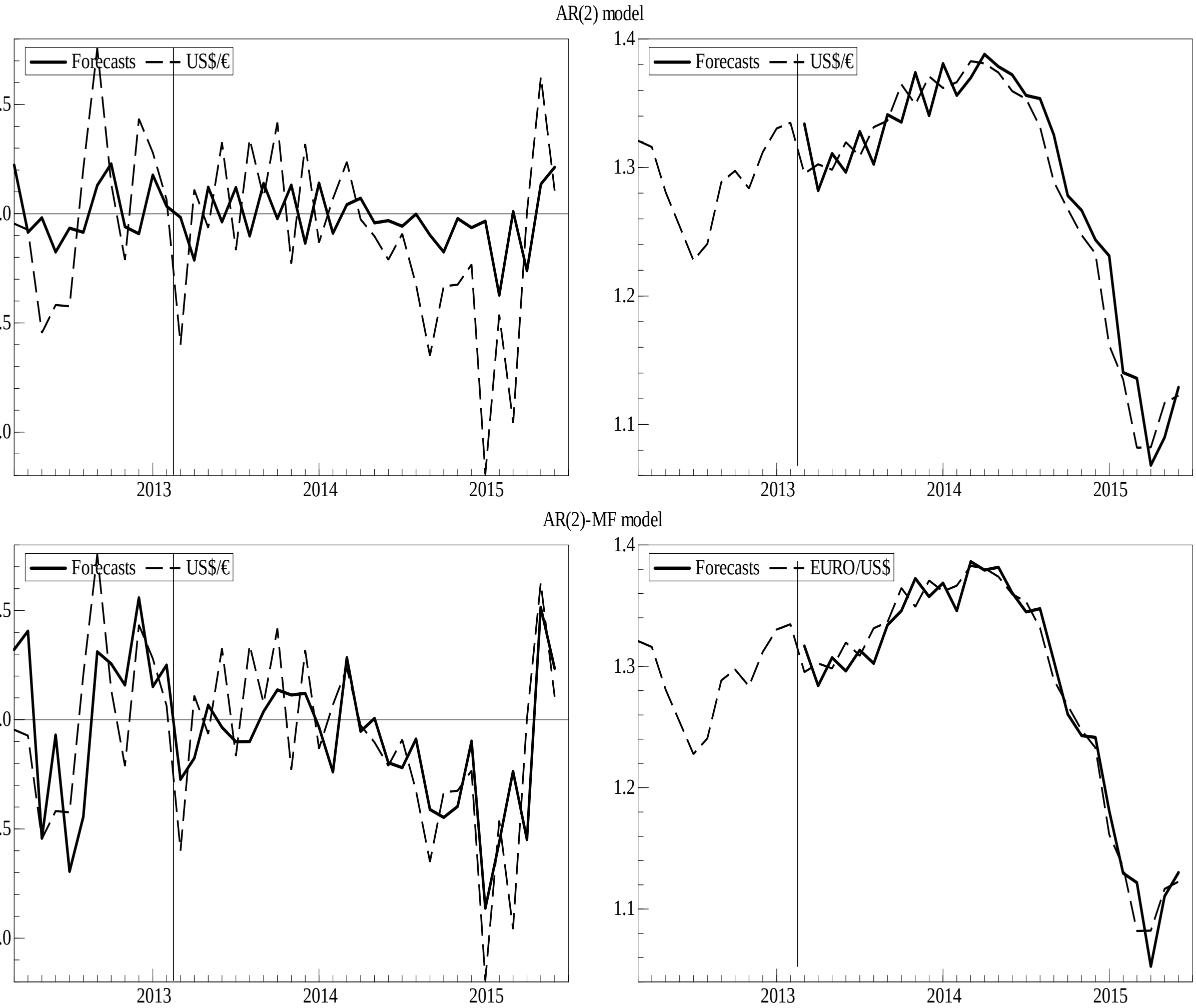

Figure 4: In the Figure 1-month ahead forecasts for both the US$/€ return (left hand side plots) and level (right hand side plots), over the post-sovereign debt crisis period, generated by means of the selected AR (top panels) and AR-MF (bottom panels) models are contrasted.

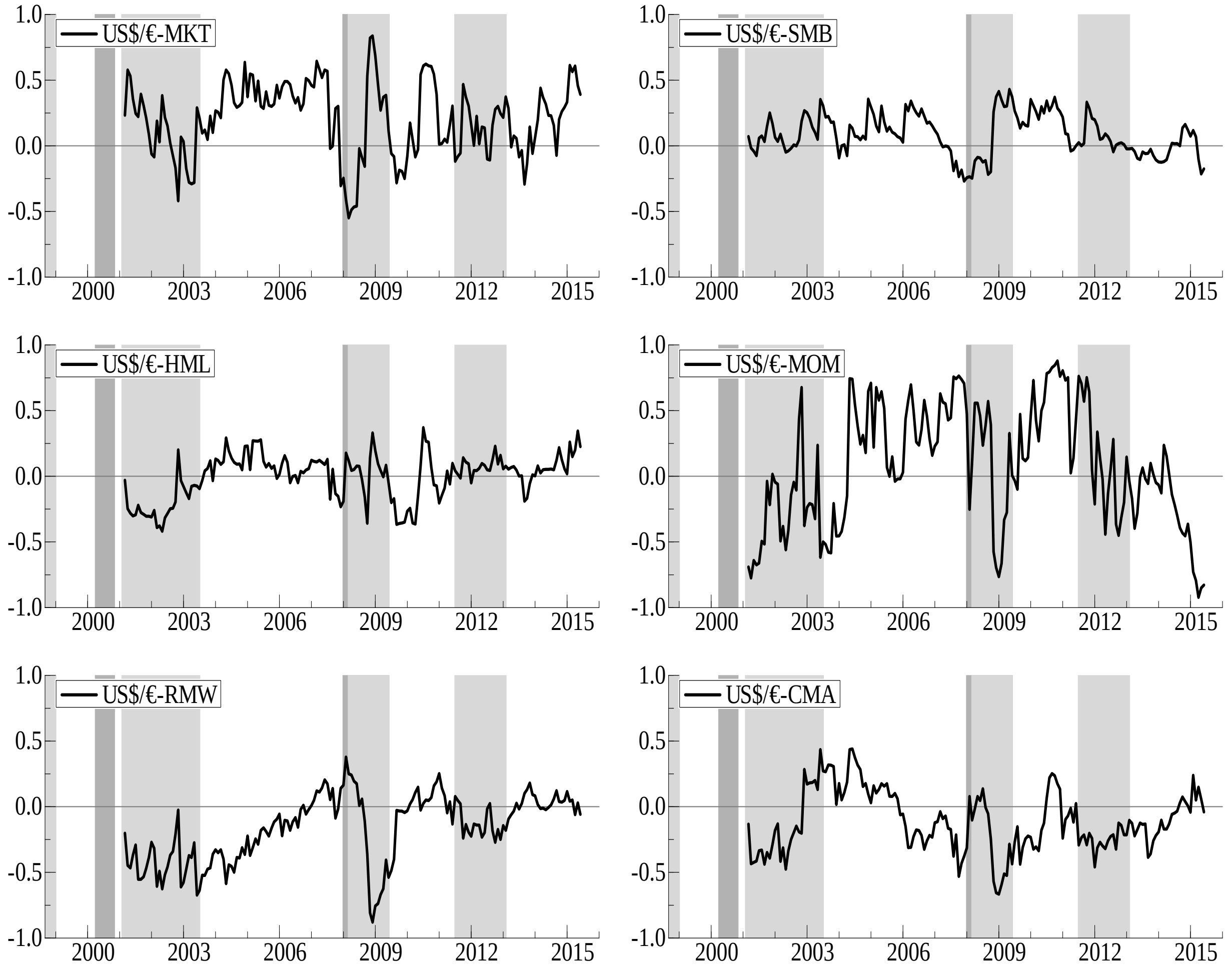

Figure 5: In the Figure conditional correlations for the US$/€ exchange rate returns with risk factors are plotted over the period 2001:1 through 2015:6. Risk factors are the Fama-French US market ($mkt_\$$), size ($smb_\$$), value ($hml_\$$), profit ($rmw_\$$) and investment ($cma_\$$) factors and Charart momentum ($mom_\$$). Shaded areas refer to recession periods for the US (darker shade) and the EA (lighter shade).

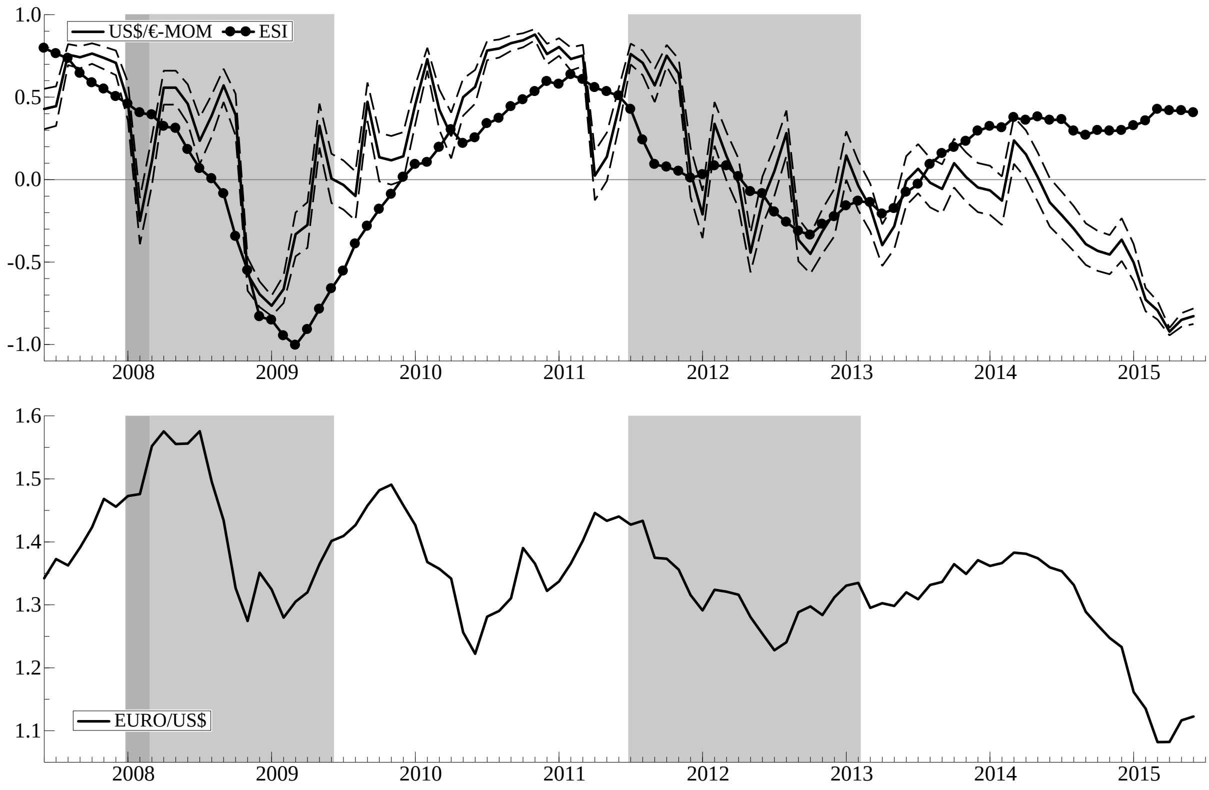

Figure 6: In the Figure, the top plot refers to the conditional correlation for the US$/€ exchange rate return with the US Charart momentum factor return, with 95% confidence interval (dashed lines), over the period 2007:6 through 2015:6. In the plot also the Economic Sentiment Indicator (ESI) released by the EU Commission is plotted for comparison. The bottom plot refers to the US$/€ exchange rate level over the same period. Shaded areas corresponds to recession periods for the US (darker shade) and the EA (lighter shade).

Supplementary Online Appendix to: "The US$/€ exchange rate: Structural modeling and forecasting during the recent financial crises"

Claudio Morana

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This Appendix presents details on the dataset used (Section A1), the computation of interest rate spread anomalies and the financial condition index for the US and the EA (Sections A2 and A3), and the ex-post correction for well-behaved conditional covariance matrix (Section A4).

A1. The data

Real Activity measures

Industrial Production for the US is the *Industrial Production Index*. It measures real output for all facilities located in the US, excluding the building sector. Data are monthly and seasonally adjusted. The source is the Board of Governors of the Federal Reserve System. Available from FRED. Industrial production for the EA is the *Production in industry - total (excluding construction) Index*. The series is monthly and seasonally adjusted. The source is Eurostat. We compute month-on-month (%) rates of growth for both series, i.e., $g_{I,€}$ and $g_{I,\$}$). The EA-US relative rate of growth of industrial production is $g_{I,€\text{-}\$} = g_{I,€} - g_{I,\$}$.

The **coincident indicator of real activity** for the US is the *Coincident Economic Activity Index for the United States*. The index is monthly and seasonally adjusted. It includes four indicators: nonfarm payroll employment, the unemployment rate, average hours worked in manufacturing and wages and salaries for 50 US States. The trend for each state's index is set to match the trend for gross state product. The source is the Federal Reserve Bank of Philadelphia. Available from FRED. A month-on-month (%) rate of growth $g_\$$ is then computed. The coincident indicator of real activity for the euro area is the *€-coin* (*C€*). It collates a large collection of statistical data (industrial production, business surveys, stock market and financial data, demand indicators, and more) and it tracks the monthly underlying quarter-on-quarter GDP growth in the euro area. The *€-coin* index is provided as quarter-on-quarter rate of growth (%). A month-on-month (%) rate of growth is computed by dividing by 3 the series at each point in time ($g_€$). The source is the Bank of Italy (CEPR Discussion Paper, No. 5633 http://www.cepr.org/pubs/new-dps/dplist.asp?dpno=5633). The EA-US relative rate of GDP growth is $g_{€\text{-}\$} = g_€ - g_\$$.

The **unemployment rate** for the US is the *Civilian Unemployment Rate*. Data are monthly and seasonally adjusted. The source is the US. Bureau of Labor Statistics. Available from FRED. The unemployment rate for the euro area is the *Unemployment rate by sex and age groups - monthly average*. Data are monthly and seasonally adjusted. The source is Eurostat. First differences of the series are computed, i.e., $u_€$, $u_\$$). The EA-US relative rate of unemployment in changes is $u_{€\text{-}\$} = u_€ - u_\$$.

Consumer and commodity prices

The **consumer price index** for the US is the *Consumer Price Index for All Urban Consumers: All-items*. It is based on prices for food, clothing, shelter, and fuels; transportation fares; service fees and sales taxes. The series is monthly and seasonally adjusted. The source is the US. Bureau of Labor Statistics. Available from FRED. The consumer price index for the euro area is the *Harmonized Consumer Price Index: All-items*. The source is Eurostat. Available from FRED. Month-on-month (%) rates of growth are computed, i.e., $\pi_€$ and $\pi_\$$. The EA-US relative rate of inflation is $\pi_{€\text{-}\$}=\pi_€ - \pi_\$$.

The **oil price** series is the *West Texas Intermediate (WTI) - Cushing, Oklahoma Spot Price* in US$ per barrel. The frequency is monthly. The source is the US. Energy Information Administration. Available from FRED. A month-on-month (%) rate of growth $o_{\$}$ is computed.

The **gold price** series is the *Gold Fixing Price 3:00 P.M. (London time) in London Bullion Market, based in U.S. Dollars* in US$ Troy Ounce. The frequency is monthly. The source is the London Bullion Market Association. Available from FRED. A month-on-month (%) rate of growth $gd_{\$}$ is computed.

The **non-energy commodities price index** is the *IMF Non-Fuel Price Index.* It includes Food and Beverages and Industrial Inputs Price Indices. The frequency is monthly. The source is the International Monetary Fund, available at http://www.imf.org/external/np/res/commod/index.aspx. A month-on-month (%) rate of growth $c_{\$}$ is computed.

Exchange rate, interest rates and monetary data

The **US$/€ exchange rate** is the *value of one Euro in U.S. Dollars.* The frequency is monthly. The source is the Board of Governors of the Federal Reserve System. Available from FRED. The month-on-month (%) log-return $\Delta e_{\$/€}$ is computed.

The **very short-term interbank rate** for the US is the *Effective Federal Funds Rate* $ov_{\$}$. The frequency is monthly (%). The source is the Board of Governors of the Federal Reserve System. Available from FRED. For the EA the series is the *EONIA* rate $ov_{€}$. The frequency is monthly (%). The source is the European Central Bank. The EA-US relative overnight rate is $ov_{€\text{-}\$} = ov_{€} - ov_{\$}$.

The **short-term Treasury Bill interest rate** for the US is the *Three-Month Treasury Bill: Secondary Market Rate* $sr_{\$}$. The frequency is monthly (%). The source is the Board of Governors of the Federal Reserve System. Available from FRED.

The **short-term interbank interest rate** for the US is the *Three-Month US Dollar Libor Rate* $li_{\$}$. The frequency is monthly (%). For the EA the series is the *Three-Month € Libor Rate* $li_{€}$. The frequency is monthly (%). The source is ICE Benchmark Administration Limited (IBA) for both series. Available from FRED. The EA-US relative short-term interbank rate is $li_{€\text{-}\$} = li_{€} - li_{\$}$.

The **libor-overnight spread** for the US $liov_{\$}$ is computed by the authors as the *Three-Month US Dollar Libor Rate* $li_{\$}$ relative to the *Effective Federal Funds Rate* $ov_{\$}$, i.e., $liov_{\$} = li_{\$} - ov_{\$}$. For the EA is computed as the *Three-Month € Libor Rate* $li_{€}$ relative to the *EONIA* rate $ov_{€}$, i.e., $liov_{€} = li_{€} - ov_{€}$. The frequency is monthly (%). The EA-US relative Libor-overnight spread is $liov_{€\text{-}\$} = liov_{€} - liov_{\$}$.

The **long-term interest rate** for the US is the *10-Year Treasury Constant Maturity Rate* $lr_{\$}$. The frequency is monthly (%). The source is the Board of Governors of the Federal Reserve System. Available from FRED. The long-term interest rates for the EA is the *Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for the Euro Area* $lr_{€}$. The frequency is monthly (%). The source is OECD, "Main Economic Indicators - complete database". Available from FRED. The relative EA-US long term rate is also computed as $lr_{€\text{-}\$} = lr_{€} - lr_{\$}$.

The **term spread** for the US $ts_{\$}$ is computed by the authors as the *10-Year Treasury Constant Maturity Rate* relative to *Three-Month Treasury Bill: Secondary Market Rate*, i.e., $ts_{\$} = lr_{\$} - sr_{\$}$ The frequency is monthly (%). For the EA the term spread $ts_{€}$ is computed as the *Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for the Euro Area* relative to the *Three-Month € Libor Rate*, i.e., $ts_{€} = lr_{€} - li_{€}$. The EA-US relative term spread is also computed as $ts_{€\text{-}\$} = ts_{€} - ts_{\$}$.

The **Aaa corporate spread** for the US $a_{\$}$ is *Moody's Seasoned Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity.* The frequency is monthly (%). The source is the Federal Reserve Bank of St. Louis. Available from FRED.

The **Baa corporate spread** for the US $b_{\$}$ is *Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity.* The frequency is monthly (%). The source is the Federal Reserve Bank of St. Louis. Available from FRED.

The **Aaa-Baa corporate spread** for the US $ba_{\$}$ is computed by the authors as the *Moody's Seasoned Aaa Corporate Bond Yield* relative to the *Moody's Seasoned Baa Corporate Bond Yield.* The frequency is monthly (%), i.e., $ba_{\$} = b_{\$} - a_{\$}$, as both $a_{\$}$ and $b_{\$}$ are relative to $lr_{\$}$.

The **very long-term interest rate** for the US $vlr_{\$}$ is the *30-Year Treasury Constant Maturity Rate.* The frequency is monthly (%). The source is the Board of Governors of the Federal Reserve System. Available from FRED. The 30-year Treasury constant maturity series was discontinued on February 2002, and reintroduced on February 2006. Missing observations are interpolated by the authors using the *20-Year Treasury Constant Maturity Rate.*

The **mortgage rate** for the US $mr_{\$}$ is the *30-Year Conventional Mortgage Rate.* It is the contract interest rates on commitments for fixed-rate first mortgages. The frequency is monthly (%). The source is the Primary Mortgage Market Survey data provided by Freddie Mac. Available from FRED.

The **mortgage spread** for the US $mb_{\$}$ is computed by the authors as the *30-Year Conventional Mortgage Rate* relative to the *30-Year Treasury Constant Maturity Rate*, i.e., $mb_{\$} = mr_{\$} - vltr_{\$}$.

Liquid liabilities for the US is the *M2 Money Stock* series in Billions of US$. It consists of M1 (currency outside the U.S. Treasury, Federal Reserve Banks, and the value of depository institutions; traveler's checks of nonbank issuers; demand deposits; and other checkable deposits) plus: savings deposits (which include money market deposit accounts); small-denomination time deposits (time deposits in amounts of less than $100,000); balances in retail money market mutual funds. Data are monthly and seasonally adjusted. The source is the Board of Governors of the Federal Reserve System. Available from FRED. M3 for the US is not available over the whole period investigated. Liquid liabilities for the euro area is the *M3 for Euro Area* series in Billions of €. It consists of M1(currency in circulation and overnight deposits) plus: M2 (deposits with agreed maturity up to two years and deposits redeemable at notice up to three months), repurchase agreements, money market fund shares and money market paper, and debt securities up to two years. Data are monthly and seasonally adjusted by the authors using X-12 ARIMA. The source is the International Monetary Fund, International Financial Statistics. Available from FRED. Month-on-month (%) rates of growth $m_{€}$ and $m_{\$}$ are computed. Then an excess real money balance rate of growth is computed as $em_{€} = m_{€} - \pi_{€} - g_{€}$ and $em_{\$} = m_{\$} - \pi_{\$} - g_{\$}$. The EA-US relative excess real money balances growth rate is computed as $em_{€\text{-}\$} = em_{€} - em_{\$}$.

For all the above exchange rate, interest rate and monetary aggregate data, monthly figures are averages of observations through period.

Balance of Payment data

Balance of Payment data are the *Trade Balance* for the US and the *Current Account Balance* for the EA, in Billions of US$ and €, respectively. Data are monthly and seasonally adjusted. The *Trade Balance* for the US is computed as the difference between *Exports of Goods and Services* and *Imports of Goods and Services*. The Trade Balance has been employed in the place of the Current Account Balance, as the latter is not available at the monthly frequency for the US. The source is the Bureau of Economic Analysis. The *Current Account Balance* for the euro area is computed as the difference between credit and debit transactions, i.e., net export plus net income receipts. The source is the European Central Bank. Both series yields an approximate measure of the net position of the country relative to the rest of the world. A positive balance, i.e., *net lending* means that US or EA residents are net suppliers of funds to foreign residents; a negative balance, i.e., *net borrowing*, means the opposite. First differences of the above series $bp_{€}$ and $bp_{\$}$ are computed.

Economic policy uncertainty and financial condition measures

The **economic policy uncertainty index** is the *Economic Policy Uncertainty Index for United States* and the *Economic Policy Uncertainty Index for Europe*, provided by Baker, S.R., Bloom, N., Davis, S.J. (http://www.policyuncertainty.com/media/BakerBloomDavis.pdf). It is based on newspaper coverage, including a human audit of 10,000 newspaper articles. The index for Europe is based on news for 5 European economies (Germany, the United Kingdom, France, Italy, and Spain). The series are normalized to mean 100 from 1985-2009. An increase in the index signals higher economic policy uncertainty. The frequency is monthly. Available from FRED. The series are transformed in logarithm $epu_{€}$ and $epu_{\$}$. The EA-US relative economic policy uncertainty index is $epu_{€\text{-}\$} = epu_{€} - epu_{\$}$.

The **stock market uncertainty** series is the estimated conditional standard deviation of the Fama-French market excess returns series for the US ($mkt_{\$}$) and Europe ($mkt_{€}$), computed by the authors by means of GARCH(1,1) models. The frequency is monthly. The series are transformed in logarithm $sdmkt_{\$}$ and $sdmkt_{€}$. The EA-US relative stock market uncertainty is computed as $sdmkt_{€\text{-}\$} = sdmkt_{€} - sdmkt_{\$}$.

Alternative measures of US stock market uncertainty are also employed. The first is the *CBOE VIX (S&P500) Index*. It is based on the S&P 500 Index and estimates expected volatility by averaging the weighted prices of S&P 500 Index puts and calls over a wide range of strike prices. The frequency is monthly. The source is CBOE (http://www.cboe.com/micro/vix-options-and-futures.aspx). The series is transformed in logarithm ($vix_{\$}$). The second is the *Equity Market Uncertainty Index* provided by Baker, S.R., Bloom, N., Davis, S.J. (http://www.policyuncertainty.com/media/BakerBloomDavis.pdf). It is based on newspaper coverage, including a human audit of 10,000 newspaper articles. The series is normalized to mean 100 from 1985-2009. An increase in the index signals higher US stock market uncertainty. The frequency is monthly. Available from FRED. The series is expressed in logarithm ($emku_{\$}$).

A US stock market volatility surprise is also computes as the difference between (log) ex-post ($sdmkt_{\$}$) and (log) ex-ante volatility ($vis_{\$}$), i.e. $vs_{\$} = sdmkt_{\$} - vis_{\$}$. A positive value indicates that realized stock market volatility was higher than expected, i.e., a positive volatility surprise; a negative value means the opposite.

The **financial condition index** is the *Chicago Fed National Financial Conditions Index* $nfci_{\$}$. It measures risk, liquidity and leverage in money markets and debt and equity markets. It is constructed to have an average value of zero and a standard deviation of one over a sample period extending back to 1973. Positive values of the NFCI indicate financial conditions are tighter than on average, while negative values indicate financial conditions that are looser than on average. The **adjusted financial condition index** is the *Chicago Fed Adjusted National Financial Conditions Index* $anfci_{\$}$. It isolates a component of financial conditions uncorrelated with economic conditions to provide an update on how financial conditions compare with current economic conditions. It is constructed to have an average value of zero and a standard deviation of one over a sample period extending back to 1973. A positive value of the ANFCI indicates financial conditions that are tighter on average than would be typically suggested by economic conditions, while a negative value indicates the opposite. The frequency is monthly. The source is the Federal Reserve Bank of Chicago. Full details about indexes construction can be found at http://www.chicagofed.org/webpages/publications/nfci/index.cfm. Available from FRED.

Risk factors

The **Fama/French 5 factors** for the US are constructed using the 6 value-weight portfolios formed on size and book-to-market, the 6 value-weight portfolios formed on size and operating profitability, and the 6 value-weight portfolios formed on size and investment. The **size factor** $smb_{\$}$ (Small Minus Big) is the average return (%) on the nine small stock portfolios minus the average return on the nine big stock portfolios; the **value factor** $hml_{\$}$ (High Minus Low) is the average return (%) on the two value portfolios minus the average return on the two growth portfolios; the **profitability factor** $rmw_{\$}$ (Robust Minus Weak) is the average return (%) on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios; the **investment factor** $cma_{\$}$ (Conservative Minus Aggressive) is the average return (%) on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios; the **market factor** $mkt_{\$}$ is the return (%) on the market, value-weight return of all (usable) CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ, relative to the *risk-free* rate, measured by the three-month US Treasury Bills rate (in monthly terms). We also consider Charart **momentum factor** $mom_{\$}$, measured by the average of the returns (%) on two (big and small) high prior return portfolios minus the average of the returns on two low prior return portfolios. The portfolios are constructed monthly. Big means a firm is above the median market cap on the NYSE at the end of the previous month; small firms are below the median NYSE market cap. Prior return is measured from month -12 to - 2. Firms in the low prior return portfolio are below the 30th NYSE percentile. Those in the high portfolio are above the 70th NYSE percentile (see Fama, E.F. and K.R., French, 1993. Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33, 3-56; Fama, E.F. and K.R., French, 2015. A Five-Factor Asset Pricing Model. Journal of Financial Economics 16, 1-22. for a complete description of the factor returns). The **European market factor** $mkt_{€}$ include data for Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom converted in US\$. Data are monthly. The source is K.R. French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Stationarity properties

Preliminary to the specification of the econometric model, we assess the persistence properties of the data. To the purpose we perform ADF tests, selecting the augmentation order by means of the AIC information criterion.[1] Rejection of the non stationarity hypothesis is then found for the $US\$/€$ nominal return ($e_{\$/€}$), the EA current account balance ($bp_{€}$) and the US trade balance ($bp_{\$}$) in changes, the rate of growth of the nominal oil price ($o_{\$}$), gold price ($gd_{\$}$) and non-energy commodities price index ($c_{\$}$), the five Fama-French risk factors ($smb_{\$}$, $hml_{\$}$, $rmw_{\$}$, $cma_{\$}$, $mkt_{\$}$, $mom_{\$}$), the US stock market log volatility surprise ($vs_{\$}$), as well its constituents, i.e., the (log) conditional standard deviation of the Fama-French market returns series ($sdmkt_{\$}$) and the (log) VIX index ($vix_{\$}$); the equity market uncertainty index ($emku_{\$}$), the relative economic policy uncertainty index ($epu_{€\text{-}\$}$). Moreover, rejection is found for various differentials of EA and US variables, likewise the industrial production ($g_{I,€\text{-}\$}$) and GDP ($g_{€\text{-}\$}$) growth rates, the unemployment rate in changes ($u_{€\text{-}\$}$), the inflation rate ($\pi_{€\text{-}\$}$), the excess real money growth rate ($em_{€\text{-}\$}$).

Less clear-cut are the results for the interest rate spreads, i.e., the overnight interbank interest rate ($ov_{€\text{-}\$}$), the three-month Libor interest rate ($li_{€\text{-}\$}$), the three-month Libor-overnight rate spreads ($liov_{€}$ and $liov_{\$}$), the US TED spread ($ted_{\$}$), the EA and US term spread ($ts_{€}$ and $ts_{\$}$), the Aaa and Baa US corporate spread ($a_{\$}$ and $b_{\$}$), the Baa-Aaa US corporate spread ($ba_{€\text{-}\$}$) and the mortgage spread ($mb_{€\text{-}\$}$). Since it is the sign of the latter variables to convey relevant signals about economic and financial conditions, first differencing might lead to a critical loss of information. Anomalous (cyclical) deviations from normal (trend) values, given current economic conditions, are then computed for the

[1] Unit root test results are not reported for reasons of space; they are available upon request from the author.

latter variables, which, according to the ADF tests, are stationary. By construction, the latter contain valuable information about the state of the economic and financial cycle (See Section 2 below). Moreover, in order facilitate the specification of the econometric model, the common information contained in the estimated *interest rate spread anomalies* ($ts_{€\text{-}\$}$, $ba_{\$}$ excluded as redundant), in the various *measures of uncertainty and risk*, i.e., the (log) conditional standard deviation for the EA and US market factors ($sdmkt_{€}$ and $sdmkt_{\$}$), the (log) VIX ($vix_{\$}$) and BBD ($emku_{\$}$) US equity market uncertainty indexes, the BBD economic policy uncertainty index for the US and Europe ($epu_{\$}$ and $epu_{€}$), as well as in the *measures of EA-US relative monetary policy stance*, i.e., the relative overnight interbank interest rate spread ($ov_{€\text{-}\$}$) and the relative 3-month Libor rate spread ($liov_{€\text{-}\$}$), are subsumed into two overall indicators of financial conditions for the US and EA, respectively (See Section A.3 below).

A2. Decomposition and cyclical properties of interest rate spreads

Think of decomposing the interest rate spread series of interest $\{y_t\}$, $t = 1, .., T$, into two orthogonal components, the former given by its *normal* or *trend* process, under current economic conditions, $\{f(x_t)\}$; the latter being the *anomalous* process $\{\varepsilon_t\}$; hence,

$$y_t = f(x_t) + \varepsilon_t$$

where $f(\cdot)$ is any real valued bounded function and x_t a conditioning variable describing current economic conditions.

Most contributions to the literature have focused on the case in which the conditioning variable x_t is simply the time index $t = 1, ..., T$, where $f(t)$ is a bounded function that can take different forms, measuring recurrent or non recurrent changes in mean, with smooth or abrupt transition across regimes (see Morana, 2014, for a review). In the paper we build on the adaptive model of Baillie and Morana (2009, 2012), where $f(t)$ is a continuous and bounded function of time, specified according to a Fourier expansion, i.e.,

$$f(t) = \delta_{i,0} + \sum_{j=1}^{J} \delta_{i,s,j} \sin(2\pi jt/T) + \delta_{i,c,j} \cos(2\pi jt/T), \quad J \leq T/2. \tag{1}$$

We modify the above specification by allowing

$$f(x_t) = \delta_0 + \delta_0 x_t + \delta_0 x_t^2 + \sum_{j=1}^{J} \delta_{s,j} \sin(2\pi j \frac{\sum_{k=1}^{t} x_k}{\sum_{k=1}^{T} x_k}) + \delta_{c,j} \cos(2\pi j \frac{\sum_{k=1}^{t} x_k}{\sum_{k=1}^{T} x_k}) \qquad J \leq T/2 \tag{2}$$

where $\sum_{s=1}^{T} x_s \neq 0$, closer to the original Gallant (1984) flexible functional form.

Hence, we set up the following regression function

$$y_t = \delta_0 + \delta_0 x_t + \delta_0 x_t^2 + \sum_{j=1}^{J} \delta_{s,j} \sin(2\pi j \frac{\sum_{k=1}^{t} x_k}{\sum_{k=1}^{T} x_k}) + \delta_{c,j} \cos(2\pi j \frac{\sum_{k=1}^{t} x_k}{\sum_{k=1}^{T} x_k}) + \varepsilon_t$$

which is then estimated by OLS, granting, by construction, an orthogonal decomposition of the series of interest into the normal and anomalous components. The estimated residual $\hat{\varepsilon}_t$, i.e., the anomaly, measures the excess risk detected by the indicator, at each point in time, relative to its normal value, according to current economic conditions.

Concerning the properties of the OLS estimator in the above framework, consistent and asymptotically normal estimation can be expected under $y_t \sim I(d)$, $-0.5 < d < 0.5$. We select the number of components to be included by means of the BIC information criterion and statistical significance of the included regressors, using HACSE, according to a *general to specific* model reduction approach. The maximum order of the expansion is set to $J = 5$.

For expository purposes the series are standardized and plotted in Figures A.1 and A.2; shaded areas refer again to recession or financial crisis periods. As is shown in the plots, eyeball inspection suggests that the estimated anomalies are stationary, property confirmed by the ADF test.[2]

[2]For reason of space we do not report details of for the estimated regressions, which are available upon request from the author.

Valuable information can be gauged by their decomposition. For instance, concerning recession periods, shrinking term spread anomalies ($ts_{\$}$, $ts_{€}$), down to *lower than normal* values, were leading the early and late 2000s financial crises and recessions for both countries; the latter then revert to normal values toward the end of the late 2000s recession and subprime financial crisis, consistent with the well known business cycle leading indicator property of the term spread (see, for instance, Fama and French, 1989). Also coherent is the signal yield by the *relative term spread* anomaly ($ts_{€\text{-}\$} = ts_{€} - ts_{\$}$), pointing to weaker expected economic conditions in the US than in the EA during the initial phase of the early 2000s recession, when actually only the US economy is in recession; the opposite condition is signalled subsequently, as the EA enters in recession while the US is recovering. Moreover, weaker economic conditions in the EA than in the US are signalled during most of the Great Recession, consistent with the deeper effects exercised by the crisis on the EA than the US. Similarly, corporate spreads ($a_{\$}$, $b_{\$}$ and $ba_{\$}$) show a shrinking anomaly, from positive to negative values, leading the early and late 2000s financial crises and ensuing recessions, as well as the early 2010s EA recession.

On the other hand, different information is conveyed by the mortgage ($mb_{\$}$), TED ($ted_{\$}$) and overnight ($ov_{\$}$, $ov_{€}$) spread anomalies. For instance, the mortgage spread points to increasing stress in the US mortgage market, persisting throughout the subprime financial crisis. Interestingly, a sharply rasing mortgage spread is also leading the burst of the dot-com bubble. Moreover, stress in the money market, i.e., raising credit and liquidity risk, is also signalled by the TED and overnight spreads throughout the subprime financial crisis period. The EA overnight spread is then sharply rising again throughout the EA sovereign debt crisis. Similar information is provided by the relative overnight spread ($ov_{€\text{-}\$} = ov_{€} - ov_{\$}$), and the relative three-month Libor spread anomaly ($liov_{€\text{-}\$} = liov_{€} - liov_{\$}$).

A3. Indicators of economic and financial distress

In the light of the above evidence we expect interest rate spread anomalies to covey relevant information, in addition to other relevant variables, for the construction of a composite indicator of business and financial cycle conditions.

In addition to the above anomalies ($ts_{€\text{-}\$}$, $ba_{\$}$ excluded as redundant), the information set selected for the construction of the indicator is comprised of various measures of stock market uncertainty and risk, i.e., the estimated log conditional standard deviation of the Fama-French market return series ($sdmkt_{€}$ and $sdmkt_{\$}$), the log VIX index ($vix_{\$}$), the log BBD equity market uncertainty index ($emku_{\$}$), the BBD-economic policy uncertainty index for the US end Europe ($epu_{\$}$ and $epu_{€}$), as well as measures of EA-US relative monetary policy stance, i.e., the relative overnight interbank interest rate spread ($ov_{€\text{-}\$}$) and the relative 3-month Libor rate spread ($liov_{€\text{-}\$}$).

The information set is then comprised of a total of sixteen variables, providing a broad coverage of financial market conditions. We then apply Principal Components Analysis (PCA), in order to subsume in few orthogonal indexes the information content of the data.

Results are reported in Table A.1, showing the estimated eigenvalues and eigenvectors (multiplied by the standard deviation of the corresponding variable), which convey information on the proportion of total variance accounted by each index (PC) and its composition, respectively. As shown in the Table, the first two PCs jointly account for about 60% of total variance (41% and 17%, respectively), the remaining (idiosyncratic) components each accounting for only a small proportion of total variance (3% on average). In the light of the purpose of the analysis, we then retain only the first two PCs.

Concerning their composition, the first PC loads with positive weight the corporate spreads ($a_{\$}$ and $b_{\$}$), whose increase signals higher risk in the corporate sector; the term spread anomalies ($ts_{\$}$, $ts_{€}$), whose increase points to higher credit risk in the Treasury bond market; the EA Libor-overnight spread anomaly ($ov_{€}$), whose increase signals growing liquidity and credit risk in the money market; all of the stock market uncertainty and risk measures ($stdmkt_{€}$, $stdmkt_{\$}$, $vix_{\$}$, $emku_{\$}$), whose increase in associated with higher stock market and recession risk; both economic policy uncertainty indexes ($epu_{\$}$ and $epu_{€}$), whose increase signals higher market uncertainty concerning the implementation of economic policies; the EA-US relative overnight an three-month Libor spreads, coherent with higher money market risk in the EA relatively to the US ($ov_{€\text{-}\$}$, $liov_{€\text{-}\$}$). On the other hand, it loads with negative weight risk associated with the US mortgage and money markets ($mb_{\$}$, $ted_{\$}$, $ov_{\$}$), netting it out, as being already accounted in the money market risk measures included, i.e., the EA Libor overnight spread anomaly ($ov_{€}$, $ov_{€\text{-}\$}$, $liov_{€\text{-}\$}$). Moreover, the second PC loads with positive weight the mortgage and money markets anomalies ($mb_{\$}$, $ted_{\$}$, $ov_{\$}$ and $ov_{€}$), the stock market uncertainty measures ($stdmkt_{€}$, $stdmkt_{\$}$, $vix_{\$}$, $emku_{\$}$), virtually omitting or netting out corporate, term spread, economic policy uncertainty and the EA-US relative money market spreads.

Closer inspection shows that the first PC (PC1) might be interpreted as an EA overall financial conditions index ($fc_{€}$); it tracks very accurately, pointing to distress, all of the episodes in which the

EA was either in recession or in financial crisis, or in both; on the other hand, the second PC bears the interpretation of US financial conditions index ($fc_{\$}$), well tracking all of the episodes of economic and/or financial distress for the US (See Figure 1 in the main text of the paper).

The latter interpretation is supported also by comparing the second principal componet (PC2) with the Chicago Fed US Net Financial Condition Index, in both adjusted ($ANFCI$) or not adjusted ($NFCI$) versions. PC2 ($fc_{\$}$) almost overlaps with both Chicago Fed indicators, being also sizably positively correlated with them (0.60; the correlation coefficient between $NFCI$ and $ANFCI$ is 0.70); it also yields similar signals concerning raising and fading economic and financial distress over time.

In order to assess the excess information contained in the Chicago Fed Indexes, we have added both indicators in our information set and repeated PCA. Results are reported in Table A.1. As is shown by the estimated eigenvectors, $NFCI$ only enters the first PC with positive weight, while both $ANFCI$ and $NFCI$ enter, still with positive weight, in the second PC. Their contribution turns out however to be negligible, as the *new* and *old* PC1 and PC2 are virtually overlapping (not reported) and almost perfectly correlated (0.95).

A4. Ex-post correction for well-behaved conditional covariance and correlation matrices

In order to ensure well behaved conditional covariance and correlation matrices, the following ex-post correction can be implemented (Morana, 2015). Firstly, the estimated conditional correlations in $\hat{R}_t$, $\hat{\rho}_{i,j}$, $i \neq j$, are bounded to lie within the range $-1 \leq \hat{\rho}_{i,j} \leq 1$ by applying the sign-preserving bounding transformation

$$\hat{\rho}^*_{i,j} = \hat{\rho}_{i,j}(1 + \hat{\rho}^k_{i,j})^{-1/k} \tag{3}$$

where $k > 0$ and even, is selected optimally by minimizing the sum of Frobenious norms over the temporal sample

$$\min_k \sum_{t=1}^{T} \left\| \hat{R}_t - \hat{R}^*_t \right\|_F = \min_k \sum_{t=1}^{T} \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} \left| \hat{\rho}_{i,j,t} - \hat{\rho}^*_{i,j,t} \right|^2}. \tag{4}$$

This yields $\hat{R}^*_t$, the transformed correlation matrix, which satisfies, by construction, the Cauchy-Schwarz inequality. Secondly, positive definiteness can be enforced by means of nonlinear shrinkage of the negative eigenvalues of the $\hat{R}^*_t$ matrix toward their corresponding positive average values over the temporal sequence in which they are positive. In practice, the eigenvalue-eigenvector decomposition of the transformed conditional correlation matrix $\hat{R}^*_t$ is performed, yielding

$$\hat{R}^*_t = \hat{E}_t \hat{V}_t \hat{E}'_t$$

where $\hat{V}_t$ is the diagonal matrix containing the ordered original (positive and negative) eigenvalues along the main diagonal and $\hat{E}_t$ is the matrix containing the associated orthogonal eigenvectors. By denoting $\hat{V}^*_t$ the diagonal matrix containing the ordered original and shrank positive eigenvalues, the new estimate of the conditional correlation matrix can be computed

$$\hat{R}^{**}_t = \hat{E}_t \hat{V}^*_t \hat{E}'_t \tag{5}$$

which, by construction, is well-behaved at each point in time. The implied, well-behaved conditional covariance process at time period t is then

$$\hat{H}^{**}_t = \hat{D}_t \hat{R}^{**}_t \hat{D}_t$$

which obeys the Cauchy-Schwarz inequality and the positive definiteness condition, at each point in time, by construction.

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Table A.1: Principal components estimation of common anomaly factors

	Basic set		Augmented set	
	PC1	**PC2**	**PC1**	**PC2**
exp var (%)	**41.31**	**17.13**	**37.80**	**20.68**
Variables	**PC1**	**PC2**	**PC1**	**PC2**
$a_{\$}$	0.3014	-0.074	0.2895	-0.1084
$b_{\$}$	0.2849	0.0005	0.2760	-0.0452
$ov_{€}$	0.0590	0.3548	0.0781	0.2937
$mb_{\$}$	-0.2496	0.3194	-0.2272	0.2877
$ted_{\$}$	-0.1539	0.4164	-0.1309	0.3616
$ov_{\$}$	-0.0259	0.3600	-0.0107	0.2846
$ts_{\$}$	0.2694	-0.1920	0.2546	-0.1713
$ts_{€}$	0.1799	-0.3785	0.1562	-0.3278
$vix_{\$}$	0.2399	0.3291	0.2574	0.2732
$emku_{\$}$	0.1939	0.3126	0.2018	0.1832
$epu_{€}$	0.2813	-0.0535	0.2701	-0.0948
$epu_{\$}$	0.3304	0.0292	0.3267	-0.0092
$sdtmk_{\$}$	0.2772	0.2208	0.2874	0.1706
$sdtmk_{€}$	0.3168	0.1094	0.3224	0.0863
$ov_{€-\$}$	-0.2913	0.0955	0.2884	0.0114
$liov_{€-\$}$	-0.2957	0.0586	0.2903	-0.0237
$NFCI$			0.1867	0.3859
$ANFCI$			0.0183	0.4065

In the Table, columns 1 and 2, first row, report the proportion of explained total variance by the first two principal components (PC1 and PC2) extracted from the set of estimated interest rate spread anomalies, uncertainty measures and monetary policy stance indicators. The successive two columns report the same information for an augmented set of variables, including, in addition to the previous ones, also the Chicago Fed Net Financial Condition Index (*NFCI*) and Adjusted Net Financial Condition Index (*ANFCI*). The entries in the associated eigenvectors are reported in rows 2 through 19 (column 1 and 2) and 2 to 21 (column 3 and 4), respectively. The basic set of indicators is composed of the Aaa and Baa US corporate spread ($a_{\$}$ and $b_{\$}$), the US and EA overnight spreads ($ov_{\$}$ and $ov_{€}$), the mortgage spread ($mb_{\$}$ }, the US and EA term spreads ($ts_{\$}$ and $ts_{€}$) , the VIX index ($vix_{\$}$), the relative overnight interbank interest rate ($ov_{€-\$}$), the relative three-month Libor interest rate ($liov_{€-\$}$), the (log) equity market uncertainty index ($emku_{\$}$), the (log) US and EA economic policy uncertainty index ($epu_{€}, epu_{\$}$), the (log) conditional volatility of the Fama-French US and EU stock market return factor ($sdtmk_{\$}$ and $sdtmk_{€}$).

Table A.2: Conditional mean specification for risk factors

Panel A: Reduced form whole sample regression: risk factors						
	$mkt_{\$}$	$smb_{\$}$	$hml_{\$}$	$rmw_{\$}$	$cma_{\$}$	$mom_{\$}$
μ	0.7906 (0.2397)	0.2744 (0.1865)	0.2169 (0.1764)	0.1622 (0.1382)	0.0914 (0.1198)	0.2421 (0.1915)
ω	0.9021 (0.7203)	0.4238 (0.2411)	0.5478 (0.2740)	0.1602 (0.0911)	0.1031 (0.0533)	0.9601 (0.4313)
ε_{t-1}^2	0.2227 (0.0933)	0.0924 (0.0386)	0.1879 (0.0995)	0.1270 (0.0507)	0.0959 (0.0366)	0.5227 (0.2050)
h_{t-1}	0.7319 (0.1026)	0.8397 (0.0425)	0.7111 (0.1052)	0.8256 (0.0446)	0.8544 (0.0311)	0.5504 (0.0940)

Panel B: misspecification tests for standardized residuals						
	$mkt_{\$}$	$smb_{\$}$	$hml_{\$}$	$rmw_{\$}$	$cma_{\$}$	$mom_{\$}$
$Q(20)$	0.6339	0.7827	0.3530	0.0601	0.5435	0.4382
$Q_2(20)$	0.9522	0.7897	0.6620	0.4624	0.4114	0.6305
$ARCH\ 1-7$	0.8135	0.7152	0.1802	0.8922	0.3170	0.9216
BJ	0.0285	0.6452	0.4095	0.0082	0.3383	0.0001
$S\&B$	0.0088	0.5283	0.9698	0.9165	0.1386	0.4582

In the Table, Panel A, we report whole sample estimates of GARCH(1,1) models for risk factor returns, i.e., the Fama-French US market ($mkt_{\$}$), size ($smb_{\$}$), value ($hml_{\$}$), profit ($rmw_{\$}$) and investment ($cma_{\$}$) factor returns, as well as Carhart momentum ($mom_{\$}$) returns. In the Table, h_{t-1} denotes the lagged conditional variance, ε_{t-1}^2 the lagged squared conditional mean residual, ω the the intercept in the conditional variance equation and μ the intercept in the conditional mean equation. In Panel B the p-value of standard misspecification test statistics are reported for the standardized residuals, i.e., the Box-Ljung test for serial correlation in standardized residuals ($Q(20)$) and squared standardized residuals ($Q_2(20)$) up to the 20th order; the joint Engle-Ng sign and size bias test ($S\&B$), the Engle ARCH effects test ($ARCH$) and the Bera-Jarque normality test (BJ).

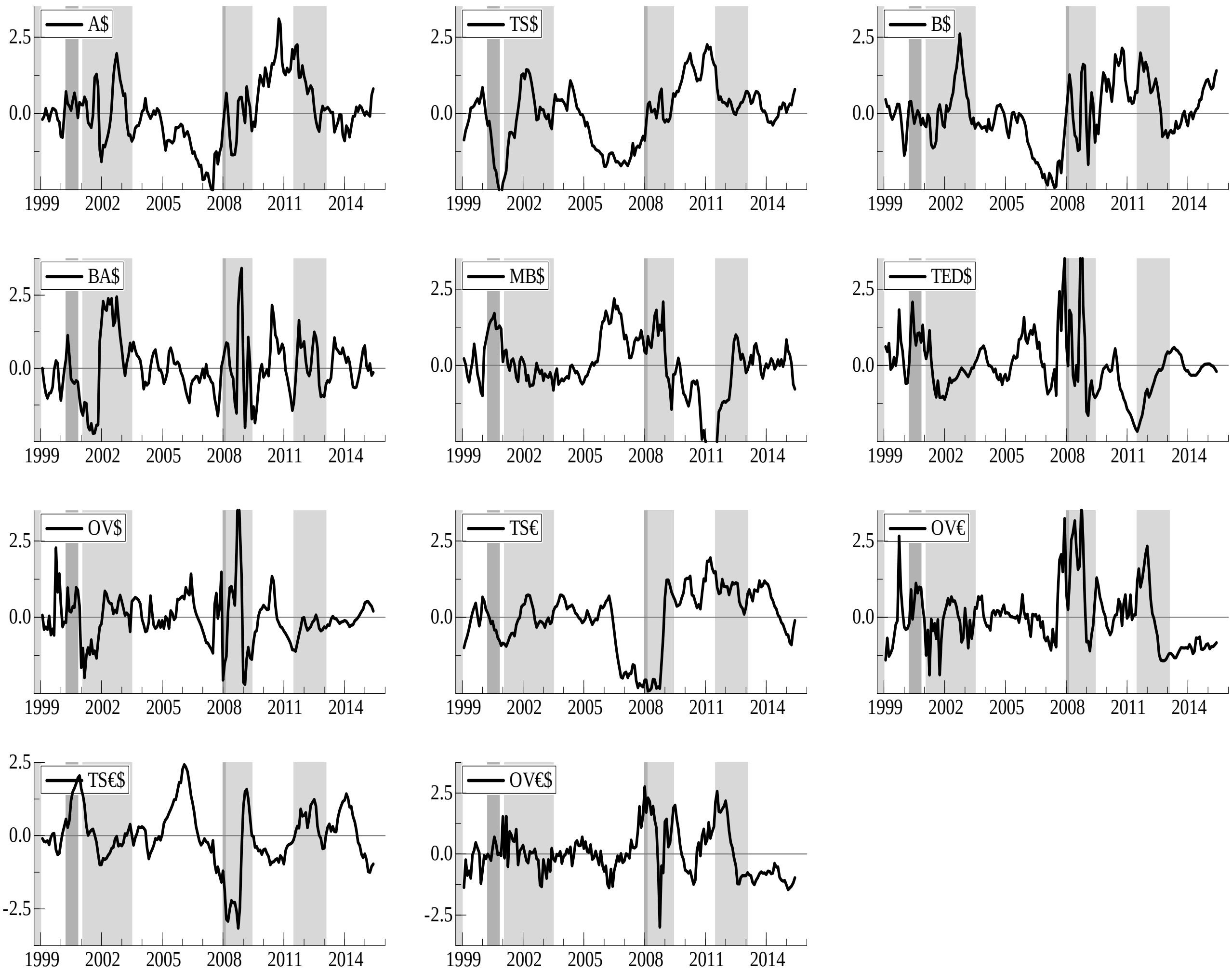

Figure A1: In the figure we plot the estimated interest rate spread anomalies. The plotted series are the US AAA and BAA corporate spreads (A$ and B$); the US BAA-AAA corporate spread (BA$), the US mortgage spread (MB$), the US and EA term spreads (TS$ and TS€), as well as their difference (TS€$); the US Ted spread (TED$); the US and EA overnight spreads (OV$ and OV€), as well as their difference (OV€$). Shaded area refer to recession periods for the US (darker shade) and the EA (lighter shade).

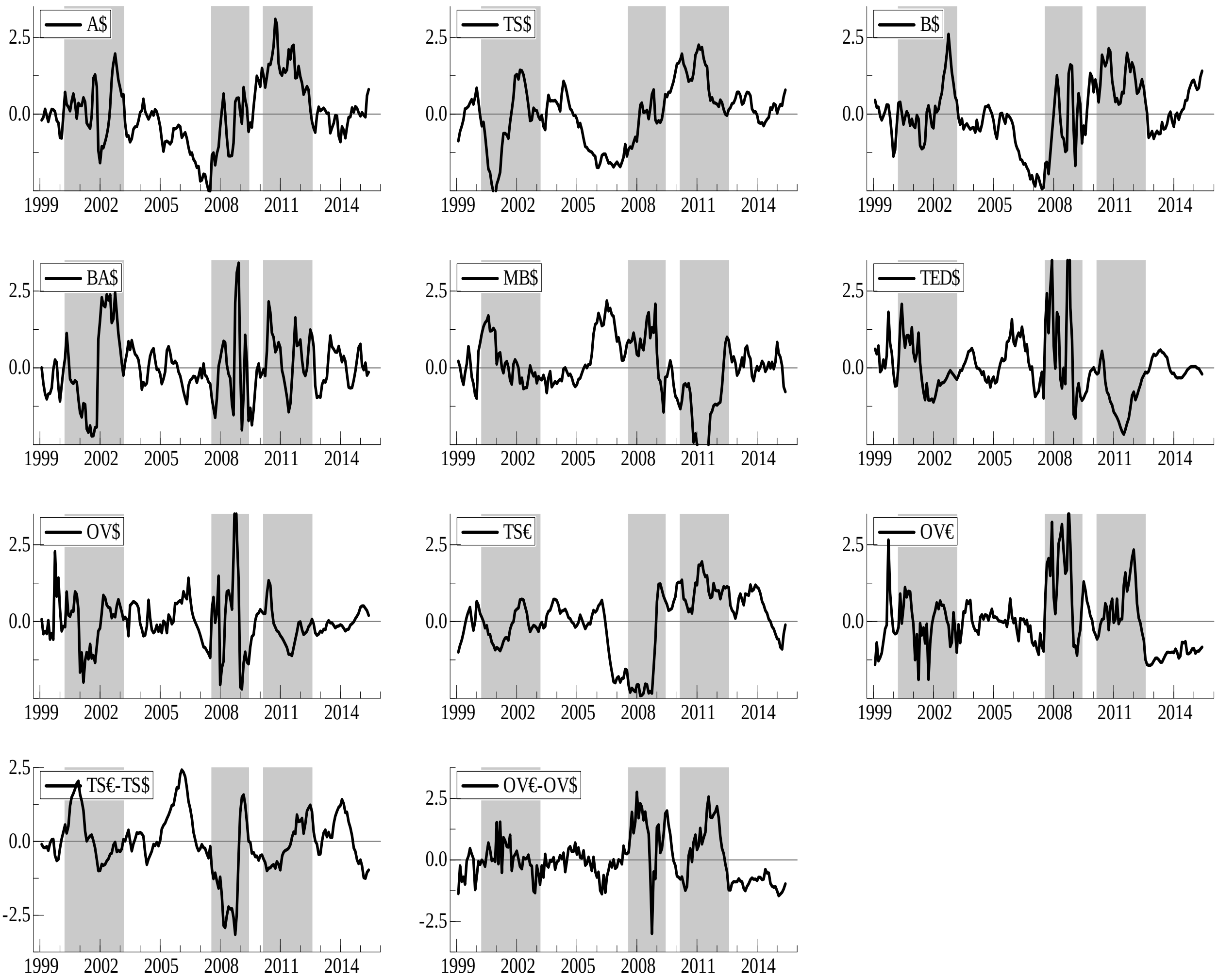

Figure A2: In the figure we plot the estimated interest rate spread anomalies. The plotted series are the US AAA and BAA corporate spreads (A$ and B$); the US BAA-AAA corporate spread (BA$), the US mortgage spread (MB$), the US and EA term spreads (TS$ and TS€), as well as their difference (TS€$); the US Ted spread (TED$); the US and EA overnight spreads (OV$ and OV€), as well as their difference (OV€$). Shaded area refer to financial crises periods for the US and the EA.

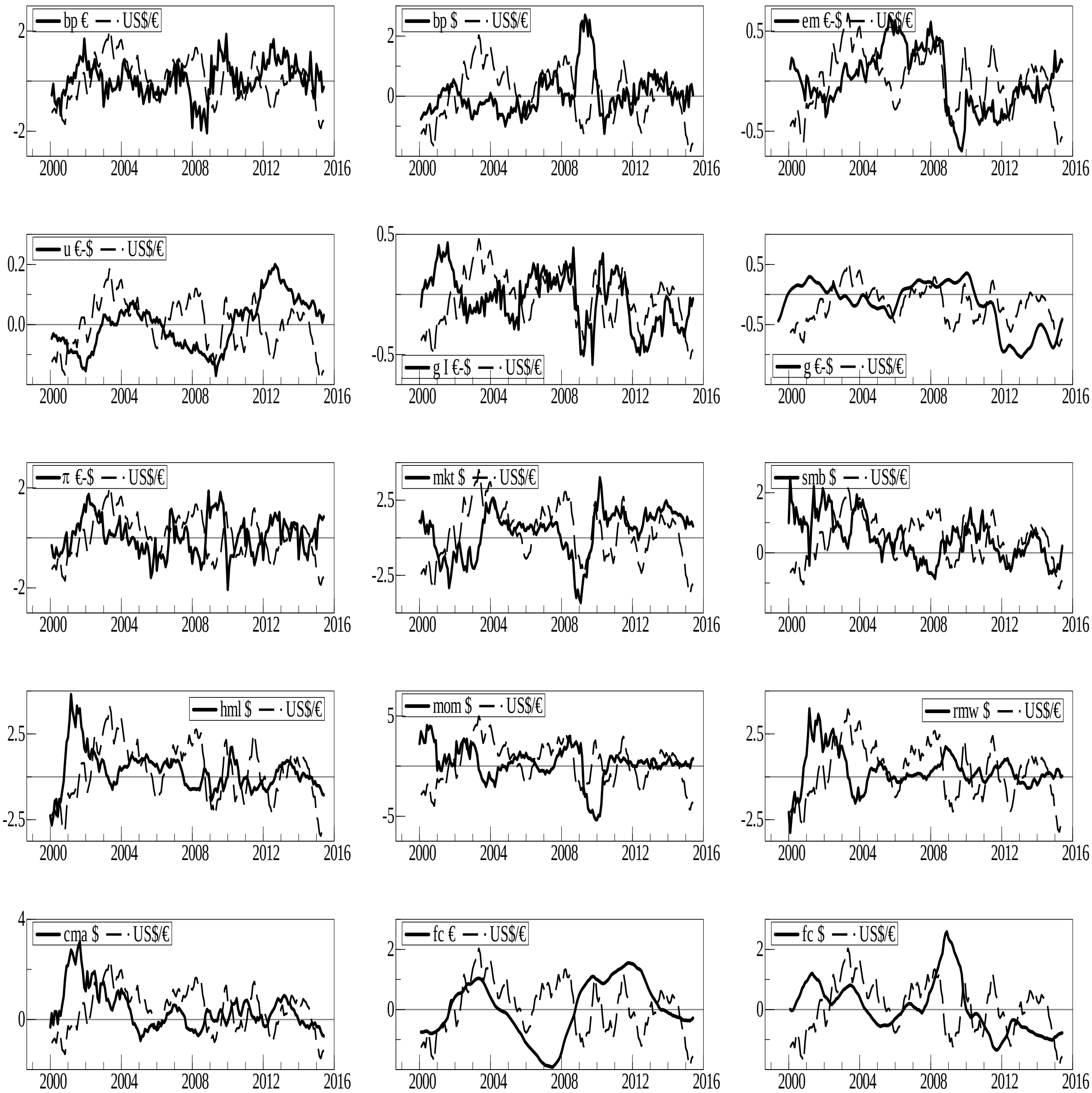

Figure A3: In the plots MA(12) smoothed macroeconomic and financial factors are plotted against MA(12) smoothed US$/€ exchange rate returns (US$/€). The variables are the EA and US current account in changes ($bp_{€}$, $bp_{\$}$), the real excess money growth differential ($em_{€-\$}$), the unemployment rate differential in changes ($u_{€-\$}$), industrial production ($g_{I,€-\$}$) and GDP ($g_{€-\$}$) growth rate differentials, the inflation rate differential ($\pi_{€-\$}$), the EA and US financial condition indexes ($fc_{€}$, $fc_{\$}$), the Fama-French US market ($mkt_{\$}$), size ($smb_{\$}$), value ($hml_{\$}$), profit ($rmw_{\$}$) and investment ($cma_{\$}$) factors and Charart momentum ($mom_{\$}$).

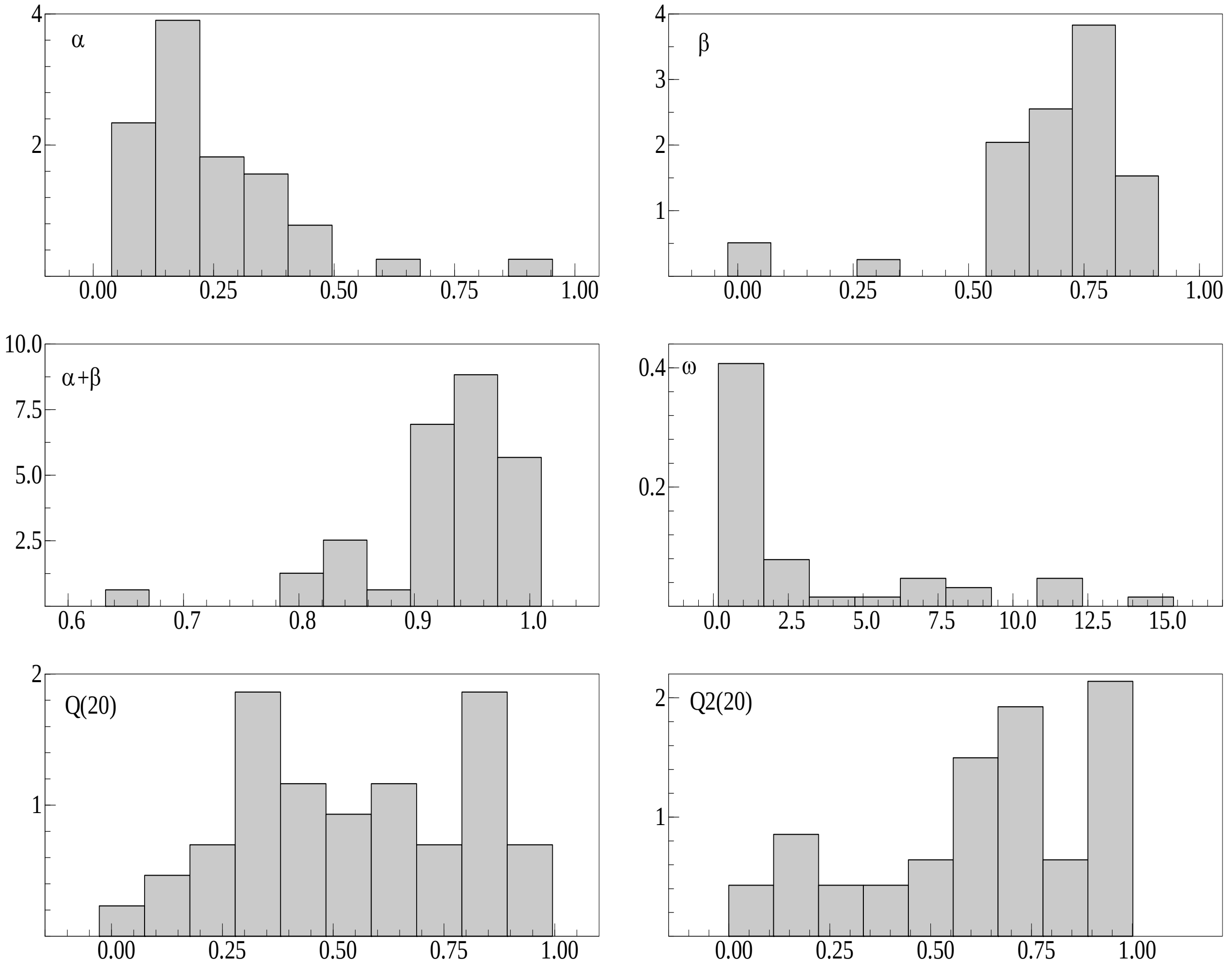

Figure A4: In the plot the cross-sectional distribution for the GARCH (1,1) estimated parameters for the composite variables are reported. In particular, ω is the conditional variance equation intercept, α is the squared lagged innovation parameter, β is the lagged conditional variance parameter, and $\alpha+\beta$ is the sum of the latter two parameters. In the plot also the cross-sectional distribution of the p-value of the Box-Ljung test for serial correlation in the standardized and squared standardized residuals (up to the 20th order) are also reported ($Q(20)$ and $Q_2(20)$).

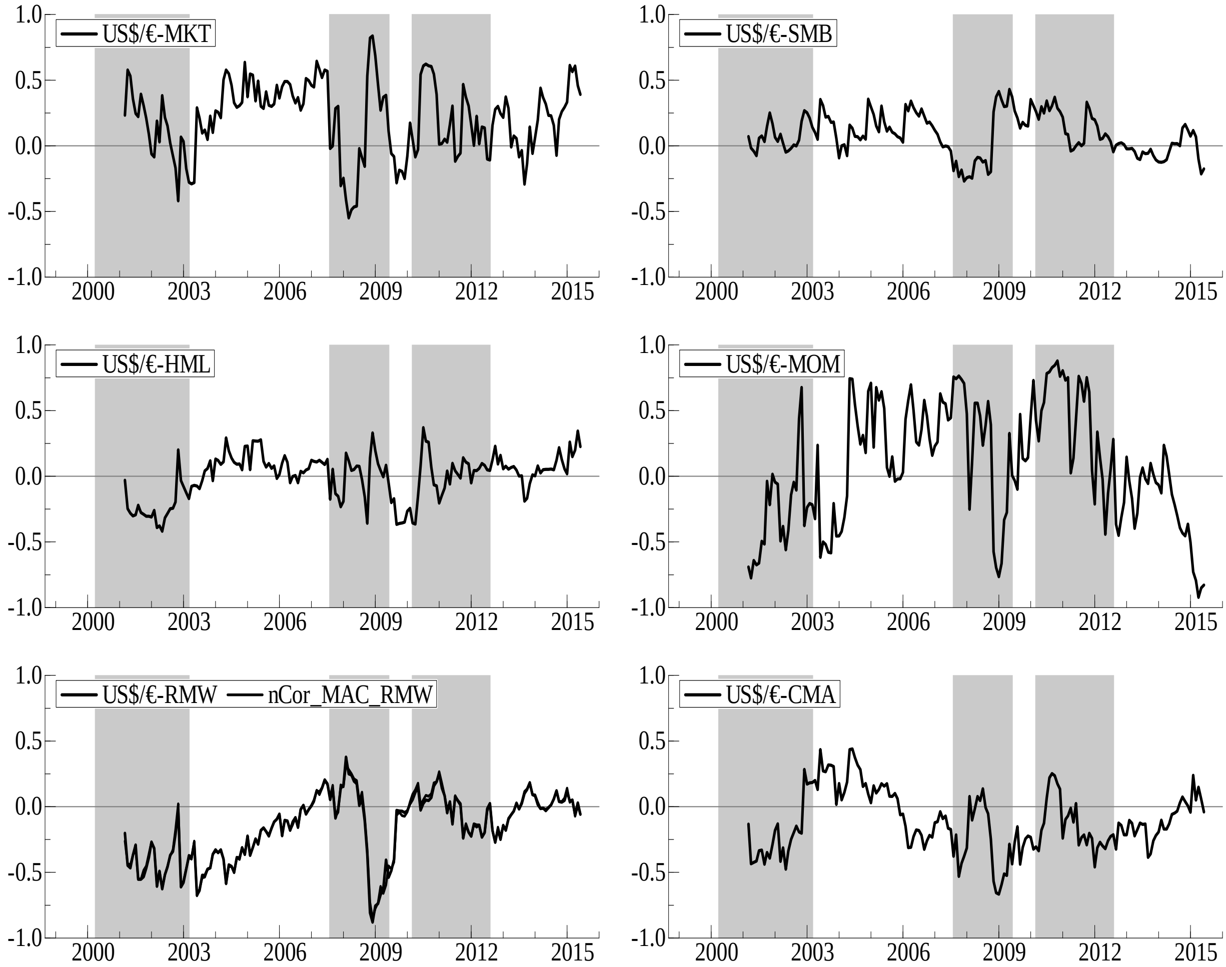

Figure A5: In the Figure conditional correlations for the US$/€ exchange rate returns with risk factors are plotted over the period 2001:1 through 2015:6. Risk factors are the Fama-French US market ($mkt_{\$}$), size ($smb_{\$}$), value ($hml_{\$}$), profit ($rmw_{\$}$) and investment ($cma_{\$}$) factors, and Charart momentum ($mom_{\$}$). Shaded areas refer to financial crises periods for the US and the EA.

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