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Abstract

The recent financial crisis has highlighted the fragility of the US financial system under several respects. In this paper, the properties of a summary index of financial fragility, timely capturing changes in credit and liquidity risk, distress in the mortgage market, and corporate default risk, is investigated over the 1986-2010 period. We find that observed fluctuations in the financial fragility index can be attributed to identified (global and domestic) macroeconomic (20%) and financial disturbances (40% to 50%), over both short- and long-term horizons, as well as to oil-supply shocks in the long-term (25%). Overall, differenty from financial shocks, macroeconomic disturbances have generally had a stabilizing effect.

Keywords: financial fragility, US, macro-finance interface, international business cycle, factor vector autoregressive models, financial crisis, Great Recession

JEL classification: C22; E32; G12

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1 Introduction

As recent global macroeconomic and financial events have powerfully shown, strong interlinkages relate financial and macroeconomic dynamics, also across countries due to financial and economic integration. Indeed, the 2007-2008 financial crisis and the ensuing “Great Recession” is an important example of a domestic (US) financial crisis, whose depressive effects quickly spilled over worldwide, amplified by the leading role of the US economy. The originating mechanism of the crisis can be traced back to excess debt creation in the US subprime mortgage market, leading to a boom-bust cycle in credit volumes and house and stock prices. Procyclical bank loans, a benign price stability environment, accommodative monetary policy, growing external debt, and deregulated financial markets all worked as amplifying mechanisms (see Bagliano and Morana, 2012 for a recent account of the crisis).

One of the likely reasons for the unprecedented depth of the crisis is the mounting fragility of the US financial sector, associated with excessive leverage and overstretching of credit. Such a phenomenon presents a number of different but interrelated dimensions, involving, among others, credit and liquidity risk conditions, the amount of stress in the mortgage market and corporate default risk perceptions. A summary measure of financial market conditions is not readily available, many indicators providing useful information on specific aspects of the financial system’s state of health.

In this paper we analyze the properties of the synthetic index of US economic and financial fragility, proposed in Bagliano and Morana (2012), obtained by combining the information conveyed by several indicators (return differentials) that are closely scrutinized by financial economists, professionals and policymakers. Specifically, we employ a Factor Vector Autoregressive econometric model to assess the relative importance of global (worldwide) factors and domestic (US) factors in determining fluctuations of the proposed US financial fragility measure over the 1986-2010 period.

The global factors include unobserved driving forces extracted from a large set of macroeconomic and financial quantities covering 50 countries and capturing worldwide developments in a wide range of real activity, labor market, liquidity, interest rates and financial price variables. In addition, a number of domestic variables are included in order to account for several sources of US financial disturbances and fundamental economic imbalances. Finally, a set of variables concerning global oil demand and supply conditions are added to allow for potential effects of oil market developments on US economic and financial conditions.

To preview the main results of the paper, we find that the bulk of fluctuations in the financial fragility index can be attributed to identified macroeconomic, financial (of both a global and local nature), and oil market structural disturbances over both a short-term and a long-term (10-year) horizons. Fundamental financial shocks yield the largest contribution, accounting for about half of the index variability in the short-term and 40% over the 10-year horizon, whereas the corresponding figures for macroeconomic disturbances are 25% and 15%, and for oil supply disturbances 5% and 25%. Moreover, the analysis of specific episodes of financial distress, occurred in 1987, 1998 and 2000, and, more recently, over the 2007-2009 period, shows that sizable fluctuations in the index are largely determined by fundamental financial shocks (risk factors shocks in particular), while macroeconomic disturbances have generally had a stabilizing effect on the fragility index. Actually, consistent with the Great Moderation phenomenon, macroeconomic shocks had a stabilizing impact on the fragility index until the occurrence of the recent financial crisis, dominating over financial shocks until the mid 1990s, and offsetting the latter thereafter.

The rest of the paper is organized as follows. In Section 2 the econometric methodology is outlined, while Section 3 describes the construction of the US financial fragility index and the data used to capture the most relevant global and local factors determining its behavior. Section 4 discusses specification issues, and Section 5 presents empirical results. Finally, the main conclusions are drawn in Section 6.

2 Econometric methodology

The complete econometric model is composed of two blocks of equations. The former describes the dynamics of the main macroeconomic and financial determinants of an index capturing the US financial system's fragility conditions (presented in detail in the following section), including both unobserved global factors and observed US variables. The second block, which is used in order to estimate the unobserved global macro-financial factors, captures the dynamics of the main macroeconomic and financial variables for a large set of developed and emerging economies. A detailed account of the methodology, briefly outlined in the present section, is provided in Appendix 1.

2.1 The econometric model

The first set of equations is composed of a number of *unobserved* ($\mathbf{F}_{1,t}$) and *observed* ($\mathbf{F}_{2,t}$) global macro-financial factors and oil market demand and supply side variables ($\mathbf{O}_t$), collected in the $r \times 1$ vector $\mathbf{F}_t = \left[\mathbf{F}'_{1,t}\ \mathbf{F}'_{2,t}\ \mathbf{O}'_t\right]'$. The second block of equations refers to q macro-financial variables for each of

m countries (for a total of $n = m \times q$ equations). The joint dynamics of the global macro-finance-oil factors and the country-specific macro-finance interactions are then modelled by means of the following reduced form dynamic factor model

$$\begin{aligned} (\mathbf{I} - \mathbf{P}(L))(\mathbf{F}_t - \boldsymbol{\kappa}_t) &= \boldsymbol{\eta}_t & (1) \\ (\mathbf{I} - \mathbf{C}(L))\left((\mathbf{Z}_t - \boldsymbol{\mu}_t) - \boldsymbol{\Lambda}\left(\mathbf{F}_t - \boldsymbol{\kappa}_t\right)\right) &= \mathbf{v}_t. & (2) \end{aligned}$$

The model is cast in a weakly stationary representation, as $(\mathbf{F}_t - \boldsymbol{\kappa}_t), (\mathbf{Z}_t - \boldsymbol{\mu}_t) \sim I(0)$, where $\boldsymbol{\mu}_t$ and $\boldsymbol{\kappa}_t$ are $n \times 1$ and $r \times 1$ vectors of deterministic components, respectively, with $r \leq n$, including an intercept, and, possibly, linear or non linear trend terms. Global dynamics are described by the stationary finite order polynomial matrix in the lag operator $\mathbf{P}(L)$, $\mathbf{P}(L) \equiv \mathbf{P}_1 L + \mathbf{P}_2 L^2 + ... + \mathbf{P}_p L^p$, where $\mathbf{P}_j$, $j = 1, .., p$, is a square matrix of coefficients of order r, and $\boldsymbol{\eta}_t \sim i.i.d.(\mathbf{0}, \boldsymbol{\Sigma}_\eta)$ is a $r \times 1$ vector of reduced form shocks driving the $\mathbf{F}_t$ factors. The contemporaneous effects of the global factors on each country variables in $\mathbf{Z}_t$ are measured by the loading coefficients collected in the $n \times r$ matrix $\boldsymbol{\Lambda} = \left[\boldsymbol{\Lambda}'_{F_1}\ \boldsymbol{\Lambda}'_{F_2}\ \boldsymbol{\Lambda}'_{O}\right]'$. Finally, $\mathbf{v}_t \sim i.i.d.(\mathbf{0}, \boldsymbol{\Sigma}_v)$ is the $n \times 1$ vector of reduced-form idiosyncratic (i.e. country-specific) disturbances, with $E\left[\eta_{jt} v_{is}\right] = 0$ for all i, j, t, s, and $\mathbf{C}(L)$ is a finite order stationary block diagonal polynomial matrix in the lag operator, $\mathbf{C}(L) \equiv \mathbf{C}_1 L + \mathbf{C}_2 L^2 + ... + \mathbf{C}_c L^c$, where $\mathbf{C}_j$, $j = 0, .., c$, is a square matrix of coefficients of order n, partitioned as

$$\underset{n \times n}{\mathbf{C}_j} = \begin{bmatrix} \underset{q \times q}{\mathbf{C}_{j,11}} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \underset{q \times q}{\mathbf{C}_{j,22}} & \cdots & \mathbf{0} \\ \vdots & \cdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \underset{q \times q}{\mathbf{C}_{j,mm}} \end{bmatrix}, \qquad (3)$$

The specification of the model in (1)-(2) embeds a set of important assumptions on the structure of global and local linkages: (i) global shocks ($\boldsymbol{\eta}_t$) affect both the global and local economy through the polynomial matrix $\mathbf{P}(L)$ and the factor loading matrix $\boldsymbol{\Lambda}$; (ii) country-specific disturbances ($\mathbf{v}_t$) do not affect global factor dynamics, limiting their impact only to the country of origin ($\mathbf{C}(L)$ is assumed to be block (own-country) diagonal).

By substituting (1) into (2), the reduced form vector autoregressive (VAR) representation of the dynamic factor model can be written as

$$(\mathbf{I} - \mathbf{A}(L))\left(\mathbf{Y}_t - \boldsymbol{\gamma}_t\right) = \boldsymbol{\varepsilon}_t \qquad (4)$$

where $\mathbf{Y}_t = [\mathbf{F}_t' \ \mathbf{Z}_t']'$, $\boldsymbol{\gamma}_t = [\boldsymbol{\kappa}_t' \ \boldsymbol{\mu}_t']'$,

$$\mathbf{A}(L) = \begin{pmatrix} \mathbf{P}(L) & \mathbf{0} \\ [\boldsymbol{\Lambda}\mathbf{P}(L) - \mathbf{C}(L)\boldsymbol{\Lambda}] & \mathbf{C}(L) \end{pmatrix},$$

$$\boldsymbol{\varepsilon}_t \equiv \begin{bmatrix} \boldsymbol{\varepsilon}_{1,t} \\ \boldsymbol{\varepsilon}_{2,t} \end{bmatrix} = \begin{bmatrix} \mathbf{I} \\ \boldsymbol{\Lambda} \end{bmatrix} [\boldsymbol{\eta}_t] + \begin{bmatrix} \mathbf{0} \\ \mathbf{v}_t \end{bmatrix},$$

with variance-covariance matrix

$$E\left[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\right] = \boldsymbol{\Sigma}_\varepsilon = \begin{pmatrix} \boldsymbol{\Sigma}_\eta & \boldsymbol{\Sigma}_\eta\boldsymbol{\Lambda}' \\ \boldsymbol{\Lambda}\,\boldsymbol{\Sigma}_\eta & \boldsymbol{\Lambda}\,\boldsymbol{\Sigma}_\eta\boldsymbol{\Lambda}' + \boldsymbol{\Sigma}_v \end{pmatrix}.$$

2.2 Estimation

The model is estimated by means of a two-stage approach. First, consistent and asymptotically Normal estimation of the set of equations in (2) is obtained following the iterative procedure proposed in Morana (2011a); the latter bears the interpretation of QML estimation performed by means of the EM algorithm. In the E-step the unobserved factors ($\mathbf{F}_{1,t}$) are estimated, given the observed data and the current estimate of model parameters, by means of principal components analysis (PCA); in the M-step the likelihood function is maximized (OLS estimation of the $\mathbf{C}(L)$ matrix is performed) under the assumption that the unobserved factors are known, conditioning on their E-step estimate. Convergence to the one-step QML estimate is ensured, as the value of the likelihood function is increased at each step.

The iterative procedure can be described as follows.

• An initial estimate of the r_1 unobserved common factors in $\mathbf{F}_{1,t}$ is obtained through the application of Principal Components Analysis (PCA) to subsets of homogeneous cross-country data $\mathbf{Z}_i = \{\mathbf{Z}_{i,1}, ..., \mathbf{Z}_{i,T}\}$, $i = 1, ..., r_1$, $r_1 \leq q$;[1] then, an initial estimate of the polynomial matrix $\mathbf{C}(L)$ and the factor loading matrix $\boldsymbol{\Lambda}$ is obtained by means of OLS estimation of the equation system in (2). This is performed by first regressing $\hat{\mathbf{F}}_t$ on $\boldsymbol{\kappa}_t$ to obtain $\hat{\boldsymbol{\kappa}}_t$; then the actual series $\mathbf{Z}_t$ are regressed on $\boldsymbol{\mu}_t$ and $\hat{\mathbf{F}}_t - \hat{\boldsymbol{\kappa}}_t$ to obtain $\hat{\boldsymbol{\Lambda}}$ and $\hat{\boldsymbol{\mu}}_t$; $\hat{\mathbf{C}}(L)$ is then obtained by means of OLS estimation of the VAR model for the gap variables $\mathbf{Z}_t - \hat{\boldsymbol{\mu}}_t - \hat{\boldsymbol{\Lambda}}\left(\hat{\mathbf{F}}_t - \hat{\boldsymbol{\kappa}}_t\right)$ in (2).

• Then, a new estimate of the unobserved factors ($\mathbf{F}_{1,t}$) is obtained, by means of PCA applied to the filtered variables $\mathbf{Z}_t^* = \mathbf{Z}_t - \left[\mathbf{I} - \hat{\mathbf{C}}(L)\right] \hat{\boldsymbol{\Lambda}}_* \left(\hat{\mathbf{F}}_{*,t} - \hat{\boldsymbol{\kappa}}_{*,t}\right)$, with $\hat{\mathbf{F}}_{*,t} = \left[\mathbf{F}_{2,t}' \ \mathbf{O}_t'\right]'$, $\hat{\boldsymbol{\Lambda}}_* = \left[\hat{\boldsymbol{\Lambda}}_{F_2}' \ \hat{\boldsymbol{\Lambda}}_O'\right]'$ and $\hat{\boldsymbol{\kappa}}_{*,t} = \left[\hat{\boldsymbol{\kappa}}_{F_2,t}' \ \hat{\boldsymbol{\kappa}}_{O,t}'\right]'$.

[1] For instance, a stock return global factor can be estimated by means of the application of PCA to the vector of cross-country stock return data, and so on.

• Next, a new estimate of the polynomial matrix $\mathbf{C}(L)$ and the factor loading matrix $\mathbf{\Lambda}$ is obtained as described in the initialization step. The iterative procedure is then repeated until convergence.

Second, consistent and asymptotically normal estimation of the set of equations in (1) is obtained by means of PC-VAR estimation (Morana, 2011b), treating the consistently estimated factors as observed. The latter is achieved in the following steps:

• PCA is applied to $\mathbf{x}_t \equiv \hat{\mathbf{F}}_t - \hat{\boldsymbol{\kappa}}_t$ and the first s PCs, $\hat{\mathbf{f}}_t$, are computed;

• the dynamic vector regression

$$\begin{aligned} \mathbf{x}_t &= \mathbf{D}(L)\hat{\mathbf{f}}_t + \boldsymbol{\varsigma}_t \\ \boldsymbol{\varsigma}_t &\sim I.I.D.\left(\mathbf{0}, \mathbf{\Sigma}_{\varsigma}\right), \end{aligned} \tag{5}$$

where $\mathbf{D}(L) \equiv \mathbf{D}_1 L + \mathbf{D}_2 L^2 + ... + \mathbf{D}_p L^p$ features all the roots outside the unit circle, is estimated by OLS to obtain $\hat{\mathbf{D}}(L)$;

• the (implied OLS) estimate of the VAR parameters in (1) is then obtained by solving

$$\hat{\mathbf{P}}(L)_{PCVAR} = \hat{\mathbf{D}}(L)\hat{\mathbf{\Xi}}_s',$$

where $\hat{\mathbf{\Xi}}_s$ is the matrix of the eigenvectors associated with the first s ordered eigenvalues of $\hat{\mathbf{\Sigma}}$ ($\mathbf{\Sigma} = E\left[\mathbf{x}_t \mathbf{x}_t'\right]$).

2.3 Dynamic analysis

The structural vector moving average representation for the global model in (1) can be written as

$$(\mathbf{F}_t - \boldsymbol{\kappa}_t) = \mathbf{H}_F(L)\mathbf{K}^{-1}\boldsymbol{\xi}_t, \tag{6}$$

where $\boldsymbol{\xi}_t$ is the vector of the r structural shocks driving the common factors in $\mathbf{F}_t$, i.e. $\boldsymbol{\xi}_t = \mathbf{K}\,\boldsymbol{\eta}_t$, $\mathbf{K}$ is a $r \times r$ invertible matrix, and

$$\mathbf{H}(L) \equiv \begin{pmatrix} \mathbf{H}_F(L) & \mathbf{0} \\ \mathbf{H}_{FZ}(L) & \mathbf{H}_Z(L) \end{pmatrix} \equiv \left(\mathbf{I} - \mathbf{A}(L)\right)^{-1}.$$

By assumption the structural factor shocks are orthogonal and have unit variance, so that $E\left[\boldsymbol{\xi}_t \boldsymbol{\xi}_t'\right] = \mathbf{K}\,\mathbf{\Sigma}_\eta \mathbf{K}' = \mathbf{I}_r$. To achieve exact identification of the structural disturbances, additional $r(r-1)/2$ restrictions need to be imposed. Since $\boldsymbol{\eta}_t = \mathbf{K}^{-1}\boldsymbol{\xi}_t$, imposing exclusion restrictions on the contemporaneous impact matrix amounts to imposing zero restrictions on the elements of $\mathbf{K}^{-1}$, for which a lower-triangular structure is assumed. This latter assumption implies a precise "ordering" of the common factors in $\mathbf{F}_t$. In particular, the first factor is allowed to have a contemporaneous impact on all other factors, but reacts only with a one-period lag to the other structural disturbances; instead, the last factor is contemporaneously affected by all structural shocks, having only lagged effects on all other factors. Operationally, $\mathbf{K}^{-1}$ (with the $r(r-1)/2$ zero restrictions necessary for exact identification imposed) is estimated by the Choleski decomposition of the factor innovation variance-covariance matrix $\mathbf{\Sigma}_\eta$, i.e. $\hat{\mathbf{K}}^{-1} = chol(\hat{\mathbf{\Sigma}}_\eta)$.

Forecast error variance and historical decompositions can then be obtained by means of standard formulas. Following the thick modelling strategy of Granger and Jeon (2004), median estimates of the parameters of interest, impulse responses, forecast error variance and historical decompositions, as well as their confidence intervals, robust to model misspecification, can be obtained by means of simulated implementation of the proposed estimation strategy. See Morana (2011a,b) and the Appendix for a detailed account of the econometric methodology.

3 The data

In this section we briefly describe the construction of the index of US financial fragility, and the global and local factors that we use in our empirical analysis.

3.1 A US financial fragility index

In order to investigate the relative importance of global and local factors as determinants of US financial conditions, an index intended to capture financial distress in US markets is constructed, summarizing information from three widely used indicators. In particular, following Bagliano and Morana (2012), we look at the TED spread, i.e. the differential between the 3-month LIBOR rate (Euro dollar deposit rate) and the yield on 3-month Treasury bills; being the difference between an unsecured deposit rate and a risk-free rate, the TED spread can be taken as a measure of credit and liquidity risk. Moreover, we use the $AGENCY$ spread between the yield on 30-year bonds issued by government-sponsored agencies (Freddie Mae and Fannie Mac) and 30-year Treasury bonds, capturing stress in the mortgage market. Finally, we look at the yield differential between BAA-rated and AAA-rated corporate bonds ($BAA - AAA$), providing a direct measure of corporate default risk and, more generally, a measure of investors' risk-taking attitude, since a contraction of this spread signals an increase in the demand for riskier bonds relative to safer ones. As shown in Figure 1 over the 1980-

2010 period, the three spreads strongly comove over the medium- to long-run, but display variations that are not perfectly correlated in the short-run (the contemporaneous quarterly correlation coefficients ranging from 0.6 to 0.74), suggesting that they contain different information on complementary dimensions of financial distress and perceived risk. To obtain a synthetic indicator of financial conditions, we extract the first principal component from the TED, $AGENCY$, and $BAA - AAA$ measures, which accounts for about 80% of the overall variability of the three spreads; the resulting variable, interpreted as an index of US financial fragility (FRA), is shown in Figure 1.

The behavior of the US financial fragility index over time is the result of many different economic and financial disturbances of a global and local nature. In the following empirical analysis, three sets of factors are specifically considered: global (world-wide) factors, local (US) factors and factors related to the international oil market.

3.2 Global factors

First, a set of macroeconomic and financial variables is constructed in order to capture the potential effects of world-wide economic conditions on the US financial system. To this aim, we use seasonally adjusted quarterly macroeconomic time series data for 31 advanced economies, 5 advanced emerging economies and 14 secondary emerging economies, for a total of 50 countries.[2] From this large amount of time series, 12 unobserved "global" factors, driving common macro-financial dynamics in all countries, are estimated by means of the iterative procedure described in the methodological section.

In particular, global macroeconomic conditions are captured by a *real activity factor* (Y), extracted from the real GDP, private consumption and investment growth series; an *employment factor* (E), extracted from the civilian employment growth series; an *unemployment rate factor* (U), obtained from changes in the unemployment rate series; a *real wage factor* (W), extracted from the real wage growth series; a *fiscal stance factor* (G), extracted

[2] The advanced countries are: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Taiwan, United Kingdom. The advanced emerging economies are: Brazil, Hungary, Mexico, Poland, South Africa. The secondary emerging economies are: Argentina, Chile, China, Colombia, India, Indonesia, Malaysia, Morocco, Pakistan, Peru, Philippines, Russia, Thailand, Turkey. The main data source is IMF *International Financial Statistics;* other data sources are *FRED2* (Federal Reserve Bank of St. Louis), the OECD and BIS (unofficial) house price data sets, and the International Energy Agency (IEA-OECD) data sets.

from the public expenditure to GDP ratio growth series; and a global bilateral *US$ exchange rate index* (X) obtained from the various bilateral exchange rates against the US$ returns. Monetary and financial developments are captured by a *nominal factor* (N), extracted from the inflation rate, nominal money growth, short- and long-term interest rate series; an *excess liquidity index* (L), obtained from changes in the M3(or M2) to GDP ratio and the private loans to GDP ratio series; a *real stock market price factor* (F), extracted from the real stock market price return series; a *real housing price factor* (H), extracted from the real housing price return series; a *real short-term rate factor* (SR), obtained from the real short-term interest rate series; and a *term spread factor* (TS), extracted from the term spread series. The monetary and financial factors account for a sizeable fraction of the overall variability of the relevant component series, ranging from 30% (in the case of the H factor) to 50% (F), with the exception of the excess liquidity factor L (15%), whereas the real activity, labor market and fiscal policy factors account for about 20% of the overall variability. For OECD countries the macro-financial sample extends from 1980(1) through 2010(3), while for non OECD countries only from 1995(1) through 2010(3); therefore, over the period 1980-1994, the above global factors reflect commonalities occurring across OECD countries only.

In addition, also two observed variables are included in the set of global influences on the US financial fragility index: the rates of change of the *real gold price* (GD), and of the *IMF non-energy commodities price index* (M).

3.3 US factors

Along with the global factors described above, a set of 8 US variables is added to capture several sources of US financial disturbances and fundamental imbalances, observed over the whole 1980(1)-2010(3) period. On the financial side, the US factors include: the *Fama* and *French* (1993) *size* (SMB) and *value* (HML) *factors*[3], the Carhart (1997) *momentum factor* (MOM)[4], the

[3] The size factor is the return differential between small and big size portfolios; the value factor is the return differential between high and low book-to-market-ratio portfolios. Adverse economic conditions should be reflected in negative changes of the size factor (small firms being more severely affected during downturns) and positive changes of the value factor (due to flight-to-quality effects, whereby investors shift from growth stocks to value stocks).

[4] The momentum factor is the difference between the returns on the high and low past perfomance portfolios, measured over the previous four quarters. The rationale of this factor is that, if past performance is an indicator of future returns, it can be expected to be larger over phases of economic expansion.

stocks' liquidity factor (PSL) proposed by Pastor and Stambaugh (2003)[5], changes in the S&P 500 stock return *volatility* (FV) estimated from an asymmetric GARCH(1,1) model of monthly stock returns, and the *leverage factor* (LEV) proposed by Adrian, Etula and Muir (2011)[6]. Moreover, changes in the ratio of the US *government budget deficit to GDP* (Fd) and the ratio of the US *trade deficit to GDP* (Td) have been included to capture US-specific policy and balance-of-payment factors.

3.4 Oil market factors

Finally, 10 variables concerning global oil demand and supply conditions have been included on order to capture potential effects of oil market developments on the US financial fragility index. In particular, we use data on *world oil reserves* growth (R), net *world oil production changes* (Pp, Pm for positive and negative changes respectively), *OECD oil refinery margins* growth (RM), *world oil consumption* (C) growth, *world oil inventories* (INV), the rate of change of the *real WTI oil price* (OP), changes of *nominal WTI oil price volatility* (OV), the *futures basis*, i.e. the spread between the twelve-month futures and the spot oil price over the spot oil price (FB), and the growth rate of the *"T" speculation index* (WT) proposed by Working (1960). The sample for the oil market variables extends from 1986(1) through 2010(3).

4 Model specification

The identification of the structural shocks, being the fundamental driving forces of the US financial system's conditions, has been performed by means of the Cholesky recursive identification strategy already mentioned in the methodological section, with the financial fragility index FRA ordered last, and therefore being contemporaneously affected by all other structural (global, US-specific, and oil market) disturbances. The chosen ordering for the factors rests on the following set of assumptions about contemporaneous (within-quarter) reactions.

[5] The Pastor-Stambaugh liquidity factor is constructed as a cross-sectional average of individual-stock liquidity measures, the latter being the effect of the transaction volume in one month on next month individual return.

[6] This factor is computed as the ratio of total financial assets over the difference between total financial assets and total financial liabilities of security brokers-delears as reported in Table L.129 of the US Federal Reserve Flow of Funds. It may be considered as a proxy for financial instability, i.e. the higher the ratio, the higher the fragility of the financial sector.

First, it is assumed that the oil market supply-side variables (including reserves R, net oil production changes Pm and Pp, and refinery margins RM) are determined mainly by geophysical factors that are exogenous to macro-financial market conditions at least within the quarter. Then, the block of the above mentioned four oil-supply variables is placed first, allowing refinery margins to react within-quarter to production and reserves shocks, and production reacting to reserve disturbances only.

A set of relatively slow-moving macroeconomic variables, including both global and US-specific factors, is placed next, and therefore allowed to react contemporaneously to oil market supply conditions. The chosen ordering goes from the global employment, unemployment, real activity, and fiscal policy factors (i.e. E, U, Y and G) to the US government budget and trade deficit to GDP ratios (Fd and Td), and finally to the global nominal and real wage factors (N and W). Here it is assumed that, over the business cycle, real activity is determined by labor market conditions through a short-run production function, with output growth feeding back on employment and unemployment with a (one-quarter) delay, capturing a sluggish adjustment of labor markets. Then, the global fiscal stance factor contemporaneously adjusts to business cycle conditions, featuring a (one-quarter) delayed impact on real activity. The inclusion of the US fiscal and trade deficit to GDP ratios also allows us to account for two potential sources of global imbalances; both variables are assumed to contemporaneously adjust to global business cycle conditions, consistently with the fact that, though the US have largely been a net importer over the time span investigated, they still are one of the world top exporters in many industrial sectors, including machinery and equipment, motor vehicles, aircraft and food. Global aggregate demand then feeds back to global aggregate supply and prices, that adjust (through the nominal factor following in the ordering) with a one-quarter delay. Finally, real wages contemporaneously react to all aggregate demand and supply developments.

Oil consumption C follows next in the ordering, based on the assumption that flow oil demand is contemporaneously determined by global business cycle conditions.

Finally, a set of mainly financial, relatively fast-moving, variables, comprising global and US-specific factors, is placed next, with the following ordering: the excess liquidity, real short-term rate, term spread, real housing prices, and exchange rate global factors (L, SR, TS, H and X) are followed by a sub-set of US financial variables, namely stock market volatility, the size and value Fama-French factors, the Caharart momentum factor, the liquidity factor, and the leverage factor (FV, SMB , HML, MOM, PSL, and LEV); finally, the remaining variables concerning the oil market, i.e. the Working's T speculative index, the futures market basis, oil inventories, the real oil price, and nominal oil price volatility (WT, FSP, INV, OP and OV), are followed by the non-energy commodities price index, the global real stock return factor, and gold prices (M, F and GD).

Within this last set of variables, the selected ordering implies that the liquidity stance (L), set by central banks according to the state of the business cycle, contemporaneously determines the real short-term interest rate, and affects asset prices and financial risk (captured by the size, value, momentum, stocks' liquidity and leverage factors, and stock market volatility), the latter being also a proxy for market expectations about future fundamentals. Consistently with potential leaning-against-the-wind strategies followed by monetary authorities, liquidity is allowed to react to asset prices and financial risk developments only with a (one-quarter) delay. Oil inventories (INV) contemporaneously respond to different real and financial factors, and becomes the transmission channel of financial (fundamental) and speculative (non-fundamental) oil demand shocks to the real oil price (OP), the latter disturbances being captured by the Working's-T index (WT) and the futures basis shocks (FB). Finally, real non-energy commodities price index returns, real stock market returns, and real gold price returns follow in the ordering. This allows to measure the contemporaneous spillover of oil price shocks to non-energy commodities markets and the stock market, as well as to study the interaction across various classes of assets under a portfolio allocation perspective. The ordering is also motivated by letting stock market returns embed all contemporaneous information on macro-financial and oil market conditions and gold (being a "crisis asset" whose demand is expected to be stronger during periods of economic and financial turmoil) also be affected by stock market dynamics.

Finally, as a general caveat, it should be recalled that the interpretation of the results of the forecast error variance and historical decompositions presented in the following section in terms of structural economic and financial disturbances may be sensitive to the chosen ordering of the variables. As the implied recursive structural model is exactly identified, the assumed restrictions cannot be tested. Yet, as a robustness check, pairwise weak exogeneity testing can always be carried out. A joint test, based on the Bonferroni bounds principle, carried out using the 528 possible bivariate tests, implied by the recursive structure, which can be computed out of the 33 variables, would not reject, even at the 20% significance level, the weak exogeneity null hypothesis.

5 Empirical results

Based on the identification scheme discussed in the previous section, concerning oil market demand and supply interactions, eight structural shocks are then identified, i.e. an *oil reserves* shock, *net positive* and *negative production* shocks, a *refinery margins* shock, *oil consumption* and *inventories preferences* shocks, and *other real oil price* and *nominal oil price volatility* shocks.

Moreover, eight structural macroeconomic shocks can be identified, i.e. an *aggregate demand* shock, a *labor supply* shock, a (*negative*) labor demand shock, a *productivity* shock, *US fiscal* and *trade deficit* shocks, a (global) *fiscal stance* shock, and a *core inflation* shock.

Finally, seventeen financial structural shocks are identified, i.e. an *excess liquidity* shock; a set of *speculative asset price (portfolio)* shocks, i.e. a *real stock market prices* shock, a *real housing prices* shock, a *real gold price* shock and a *real non energy commodity price index* shock; an *US$ exchange rate index* shock; a *risk-free rate* shock; two oil futures market speculative shocks, i.e. *Working's-T* and *futures basis* shocks; a set of *risk factors* shocks, measuring revisions in market expectations about future fundamentals, i.e. a *risk aversion* shock, *size*, *value*, *leverage*, *stocks' liquidity*, and *momentum* factor shocks; a *term spread* shock; a *residual economic and financial fragility index* shock. See Appendix 2 for details concerning the interpretation of the structural shocks.

We then proceed to the assessment of the relative importance of the various sources of structural disturbances in determining the behavior of the US financial fragility index. To this purpose, first a forecast error variance decomposition is performed over various horizons; second, focusing on several important episodes of financial and economic distress, the changes in the index are decomposed into the portions attributable to structural shocks of a different nature.

5.1 Forecast error variance decomposition

Median forecast error variance decompositions have been computed up to a horizon of ten years (40 quarters). Table 1 shows the results for selected horizons, that we denote, for expository purposes, as "very short-term" (2 quarters), "short-term" (between 1 and 2 years), "medium-term" (between 3 and 5 years), and "long-term" (10 years) horizons.[7] Panel A of the table shows the contribution (in percentage points) of each individual structural

[7]A full set of results is available upon request from the authors.

shock to the forecast error variance of the US fragility index at the various horizons. For ease of discussion, Panel B presents the results with reference to general categories of disturbances, distinguishing among oil market supply side shocks (SUP, including shocks to oil reserves, net negative and positive production, and refinery margins), shocks to oil demand (DEM, including disturbances to oil consumption and inventories preferences), a group of macroeconomic disturbances (MAC, including labor demand and supply, aggregate demand, the fiscal stance, the US budget and trade deficits, core inflation and productivity), a group of fundamental financial shocks (FIN, comprising excess liquidity, the risk-free rate, the term spread, housing prices, risk aversion, size, value, momentum, stocks' liquidity and leverage factors, real non-energy commodity prices, real stock prices, real gold prices, real oil price and nominal oil price volatility), US$ exchange rate disturbances (X), and speculative/non fundamental financial shocks (SPC, including the Working's-T index, and the oil futures basis). Finally, Panel B presents the results for sub-categories of macroeconomic and financial shocks, namely labor market shocks (LM: labor demand and supply), aggregate demand disturbances (Y), core inflation shocks (N), productivity disturbances (W), deficits shocks (FT: fiscal stance, US fiscal and trade deficits), liquidity and interest rate shocks (MP: excess liquidity, risk-free rate, term spread), portfolio allocation shocks (PA: real house prices, real non-energy commodity prices, real stock prices, real gold price, real oil price) and risk factors disturbances (RF: nominal oil price volatility, risk aversion, size, value, momentum, stocks' liquidity and leverage factors).

As shown in the last column of Table 1, the US fragility index is strongly endogenous, since its own shock only accounts for about 15% of total fluctuations in the very short-term and about 11% in the medium-to long-term. This finding supports the proposed interpretation of the fragility index as a synthetic measure, conveying multiple information on different factors determining the state of the financial system. Three main categories of structural shocks account for the bulk of fluctuations in the US financial fragility index. First, fundamental financial shocks (FIN) yield the largest contribution: 50% in the short-term and 40% in the long-term. Within this category, risk factors shocks (RF) are particularly relevant (34% in the very short-term and 27% in the long-term), mainly due in the very short-term to risk aversion disturbances (16%) and value factor shocks (14%), and to the size and value factor disturbances over the long-term horizon (10% and 8% respectively). Portfolio allocation shocks (PA) follow, accounting for 13% of the fragility index fluctuations over the short-term horizon and 10% in the long-term. Second, macroeconomic disturbances (MAC) yield a sizable contribution to the fragility index fluctuations, accounting for around 25% of the index variability in the very short-term, and still 15% over the longer 10-year horizon. Among macroeconomic shocks, aggregate demand (real activity) (8%), deficits (8%) and labor productivity shock (6%) are particularly important sources of fluctuations in the short-term, their relevance declining as the forecast horizon increases. Finally, oil market supply disturbances (SUP) contribute importantly to the fragility index fluctuations in the medium- to long-term (20% to 25%), negative net oil production shocks being the most relevant shock (20%). All other sources of structural disturbances play a more limited role in accounting for fluctuations in the fragility index at any forecasting horizon.

5.2 Historical decomposition

In Table 2 and Figures 2-4, changes in the level of the US financial fragility index (net of base prediction) over relevant sub-periods and specific episodes are decomposed into the portions attributable to macroeconomic and financial structural disturbances. In particular, two sub-periods are considered: 1986(4) through 2006(4), roughly corresponding to the "Great Moderation" period, preceding the 2007 financial crisis, and 2007(1) through 2010(3), covering the financial crisis and the ensuing recession. In Table 2, we also report details concerning few episodes of interest in the sample, including the 1987(4)stock market crash, the 1990(4) first Persian Gulf War and associated oil price shock, the 1998(4) East Asia crisis, the 2000(2) burst of the dot-com bubble, and the 2007-2009 financial crisis. All episodes mentioned above (and highlighted in Figure 1 by means of vertical lines and shaded areas) are characterized by a quarterly increase of over 20 b.p. in the fragility index. As for the forecast error variance decomposition, the discussion will focus on various categories of shocks, rather than on individual structural disturbances.

5.2.1 The Great Moderation period

As shown in Figure 2, over the whole 1986-2006 period, macroeconomic (MAC), financial (FIN) and oil market supply-side (SUP) disturbances have been the largest contributors the the US fragility index dynamics. In particular, with the only exception of 1990(4), all the specific episodes selected in Table 2 share some common features, being largely determined by financial shocks, which account almost entirely (80% to 95%) for the overall increase in the fragility index (ranging from 27 to 36 b.p.). In particular, risk factor shocks are always dominant (their contribution going from 16 to 23 b.p.), with portfolio disturbances also playing a role in 2000(2), and liquidity and interest rate shocks in 1987(4). Apart from the 2000(2) episode, macroeconomic disturbances have had a stabilizing effect, dampening to some extent the increase of the fragility index (ranging from -5 to -8 b.p.). Differently, the 1990(4) episode, featuring an increase in the index by 28 b.p., can be fully attributed to disturbances coming from the oil market, with oil supply, demand and speculative shocks contributing importantly (by 16, 7 and 6 b.p, respectively); also in this case, macroeconomic (and exchange rate) shocks have partially offset the increase in the fragility index (-5 b.p.).

5.2.2 The 2007-2010 crisis period

Over the 2007-2010 period, sizable increases in the fragility index, strictly related to relevant financial and economic events, are observed. For instance, the 22 b.p. and 21 b.p. increases in 2007(3) and 2007(4) can be associated with the beginning of the financial crisis in August 2007 and its aftermath, while the 27 b.p. and 102 b.p. increases in 2008(3) and 2008(4) signal the deepening of the financial crisis. Then, five remarkable contractions in the fragility index can be noted over the period 2009(1) through 2010(1), as economic and financial conditions progressively, though temporarily, improved.

As shown in Table 2 and in Figures 3 and 4, the behavior of the fragility index in the second half of 2007 is largely accounted for by financial shocks (14 b.p. and 8 b.p. respectively in 2007(3) and 2007(4)), with shocks coming from the oil market (related to both the demand and the supply side and to financial speculation) also providing a sizable contribution (12 and 8 b.p. in the two quarters). Differently, changes in the fragility index occurred in 2008(3) and 2008(4) are largely driven by macroeconomic shocks. In 2008(3) the overall 27 b.p. increase in the index is fully determined by macroeconomic disturbances, deficit and productivity shocks, accounting for 70% of the index increase; also, macroeconomic shocks account for 50% of the 49 b.p. increase in the index observed in 2008(4), with a sizeable contribution from all sources of macroeconomic disturbances, apart from expected inflation. Also financial shocks (especially attributable to portfolio allocation and risk factors) played a relevant role in the final quarter of 2008, determining an increase of the fragility index by 35 b.p. Overall, macroeconomic and financial disturbances jointly account for about 85% of the 102 b.p. increase in the fragility index in 2008(4), oil market shocks adding an additional 13 b.p. increase.

On the other hand, the 2009(1) through 2010(1) period displays progressively improving economic and financial conditions, with the fragility index falling by over 200 b.p. cumulatively, more than compensating the 2007(3)-2008(4) 170 b.p. increase. This episode is again largely driven by the identified macroeconomic and financial disturbances, which jointly account for 70% to 90% of the index contraction in 2009(1)-2009(3), 50% in 2009(4). Apart from core inflation, all macroeconomic shocks yielded a sizable contribution to fragility index downward dynamics over the investigated sub period; a similar conclusion holds for financial shocks, with risk factors shocks dominating in 2009(1) and 2009(3).

In order to gauge the effects of the macroeconomic and financial shocks on the level of the fragility index, in Figure 5 the cumulative historical decomposition, with reference to various categories of shocks, is plotted. As shown in Figure 5, over the whole period investigated, fundamental financial shocks were the major upward driver of the fragility index, while oil market-supply side shocks were stabilizing up to the mid 1990s and destabilizing thereafter. Moreover, macroeconomic shocks had, in general, a stabilizing impact, reinforcing the destabilizing effects of financial disturbances only during the subprime financial crisis and Great Recession episodes. Moreover, when the joint contribution of macroeconomic and financial shocks (the latter including non fundamental financial and exchange rate disturbances) is considered, there is evidence that macroeconomic shocks were dominating over financial disturbances up to the mid 1990s, and then sufficiently strong to offset the latter thereafter, until the occurrence of subprime crisis. Then, our results support the view that sees the recent financial crisis as marking the end of the Great Moderation period.

6 Conclusions

The recent financial crisis has highlighted the fragility of the US (and other countries') financial system under several respects. A number of indicators and financial variables are closely observed and used as signals of financial market distress. In this paper, a summary index of financial fragility is obtained by combining information conveyed by the "Agency", "Ted" and "BAA-AAA" spreads, timely capturing changes in credit and liquidity risk, distress in the mortgage market, and corporate default risk, all important elements to evaluate the solidity of the financial system. We investigate the determinants of fluctuations in the proposed index of US financial fragility over the 1986-2010 period by means of a large-scale factor vector autoregressive econometric model which allows us to consider a broad range of global (worldwide) and domestic (US) macroeconomic and financial driving forces.

The empirical analysis shows that observed fluctuations in the financial fragility index can be attributed to identified (global and domestic) macroeconomic, financial and oil-market structural disturbances, over both a short-term and a long-term (10-year) horizons. Fundamental financial shocks yield the largest contribution, accounting for 40%-50% of the index variability, whereas macroeconomic disturbances explain about 20% of fluctuations in the index, and oil-supply shocks disturbances account for an additional 25% over the long-run horizon (though explaining only 5% of the index variability in the short-run). Moreover, the historical decomposition of the changes in the index during specific episodes, including the financial market crashes occurred in 1987, 1998 and 2000, and the more recent period of financial turmoil and general economic recession (2007-2009), show that sizable fluctuations in the index are largely determined by fundamental financial shocks (related to risk factors shocks in particular), while macroeconomic disturbances have generally had a stabilizing effect. Actually, consistent with the Great Moderation phenomenon, macroeconomic shocks had a stabilizing impact on the fragility index until the occurrence of the recent financial crisis, dominating over financial shocks until the mid 1990s, and offsetting the latter thereafter. Overall, the results support our proposed macroeconomic-financial-oil market framework in modelling the determinant driving forces of US financial fragility.

References

[1] Adrian T., E. Etula and T. Muir, 2011, Financial intermediaries and the cross-section of asset returns, Federal Reserve Bank of New York Staff Reports n. 464.

[2] Bagliano, F.C. and C. Morana, 2012, The Great Recession: US dynamics and spillovers to the world economy, Journal of Banking and Finance, 36, 1, 1-13.

[3] Carhart, M., 1997, On persistence of mutual fund performance, Journal of Finance, 52, 57-82.

[4] Fama, E.F. and K.R. French, 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Econonomics, 33, 3-56.

[5] Granger C.W. and Y. Jeon, 2004, Thick modelling, Economic Modelling, 21, 323-343.

[6] Hamilton, J., 1996, This is what happened to the oil price-macroeconomy relationship, Journal of Monetary Economics, 38, 215-20.

[7] Morana, C., 2011a, Factor vector autoregressive estimation of heteroskedastic persistent and non persistent processes subject to structural breaks, available at SSRN: http://ssrn.com/abstract=1756376.

[8] Morana, C., 2011b, PC-VAR estimation of vector autoregressive models, Università di Milano-Bicocca, mimeo, available at SSRN: http://ssrn.com/abstract=.

[9] Pastor L. and R.F. Stambaugh, 2003, Liquidity risk and expected stock returns, Journal of Political Economy, 111, 3, 642-685.

[10] Working H., 1960, Speculation on hedging markets, Stanford University Food Research Institute Studies 1, 185-220.

Table 1: Forecast error variance decomposition of the fragility index: contributions of each structural shock and of categories of structural shocks

Panel A: contribution of individual structural shocks

	R	Pm	Pp	RM	E	U	Y	G	Fd	Td	N	W	C	L	SR	TS	H	X	FV	SMB	HML	MOM	PSL	LEV	WT	FB	INV	OP	OV	M	F	GD	FRA
0	4.4	0.2	0.0	0.0	4.6	0.0	8.0	0.1	3.2	1.4	1.2	6.1	1.6	0.0	0.2	0.2	1.6	0.8	15.8	0.1	13.9	1.5	0.0	0.0	0.1	5.0	0.9	0.1	2.7	10.6	0.2	0.6	15.0
2	3.6	0.7	0.5	1.7	5.7	1.4	5.4	0.9	4.0	0.9	0.8	2.4	3.7	0.2	3.4	0.2	1.1	0.4	6.4	0.5	16.2	2.3	2.2	0.3	0.1	5.3	0.5	0.9	4.8	9.7	0.1	1.1	12.7
4	3.1	1.9	0.5	1.3	4.9	1.1	5.2	0.8	4.0	1.7	0.8	3.2	3.8	1.5	5.0	0.3	1.7	0.7	4.8	0.5	15.7	1.9	3.2	0.3	0.1	4.1	0.8	0.8	3.7	7.9	0.3	0.8	13.5
6	3.2	5.3	0.4	1.1	6.0	1.0	4.1	1.9	4.9	1.3	0.6	3.4	3.1	1.8	3.7	0.4	2.9	0.6	4.2	4.0	12.8	1.3	4.2	0.3	0.1	2.9	1.4	0.6	3.0	6.0	0.9	0.6	12.2
8	2.5	9.6	0.5	0.8	6.3	1.1	2.9	2.7	4.2	1.2	0.5	2.5	3.0	1.3	2.6	0.6	3.9	0.7	3.1	7.3	11.1	1.0	4.3	0.4	0.2	2.4	1.8	0.5	3.0	5.4	1.2	0.4	11.2
12	1.9	13.1	1.4	0.9	6.2	1.1	2.1	3.8	3.5	0.9	0.5	1.7	3.0	1.2	1.8	0.8	4.3	0.9	2.1	8.8	9.2	0.7	4.1	0.5	0.3	1.9	2.3	0.4	3.0	5.0	1.3	0.3	11.0
20	2.0	16.4	1.6	0.9	5.2	1.2	1.4	3.9	2.9	0.6	0.4	1.4	3.4	1.0	1.3	1.0	4.1	1.0	1.4	9.8	8.5	0.5	4.3	0.5	0.3	1.5	2.6	0.3	2.9	4.9	1.3	0.2	11.2
40	2.2	20.2	1.8	0.7	4.5	1.3	0.8	3.3	2.8	0.3	0.2	1.5	4.1	1.0	0.9	0.9	3.8	0.7	0.8	9.9	8.4	0.3	4.6	0.4	0.3	1.3	2.5	0.3	2.9	4.6	1.3	0.1	11.1

Panel B: contribution of categories of shocks

								MAC					FIN			
	SUP	**DEM**	**MAC**	**X**	**FIN**	**SPC**	**FRA**	**LM**	**Y**	**FT**	**N**	**W**	**MP**	**PA**	**RF**	**FRA**
0	4.6	2.5	24.5	0.8	47.4	5.1	15.0	4.7	8.0	8.1	1.2	6.1	0.4	13.0	34.0	15.0
2	6.5	4.2	21.4	0.4	49.4	5.4	12.7	7.1	5.4	6.3	0.8	2.4	3.7	12.9	32.8	12.7
4	6.9	4.6	21.7	0.7	48.4	4.2	13.5	6.0	5.2	6.0	0.8	3.2	6.8	11.5	30.1	13.5
6	9.9	4.5	23.2	0.6	46.7	3.0	12.2	7.0	4.1	6.0	0.6	3.4	5.9	10.9	29.8	12.2
8	13.4	4.8	21.4	0.7	46.0	2.6	11.2	7.3	2.9	5.7	0.5	2.5	4.6	11.3	30.1	11.2
12	17.4	5.3	19.7	0.9	43.5	2.1	11.0	7.3	2.1	5.9	0.5	1.7	3.8	11.3	28.5	11.0
20	20.8	6.1	17.1	1.0	42.0	1.9	11.2	6.4	1.4	5.3	0.4	1.4	3.3	10.8	27.9	11.2
40	24.9	6.6	14.8	0.7	40.2	1.6	11.1	5.8	0.8	4.1	0.2	1.5	2.8	10.2	27.2	11.1

The table reports the forecast error variance decomposition for the fragility index at selected horizons (impact (0) and 2 to 40 quarters), relatively to the various structural shocks (Panel A): reserves (R), net negative production (Pm), net positive production (Pp), refineries margins (RM), labor supply (E), labor demand (U), aggregate demand (Y), fiscal stance (G), US fiscal deficit (Fd), US trade deficit (Td), core inflation (N), productivity (W), oil consumption (C), excess liquidity (L), risk-free rate (S), term spread (TS), real housing prices, (H), US$ exchange rate index (X), risk aversion (FV), size factor (SMB), value factor (HML), momentum factor (MOM), stocks' liquidity factor (PSL), leverage factor (LEV), Working-T index (WT), futures basis (FB), inventories (INV), real oil price (OP), oil price volatility (OV), real non-energy commodity prices (M), real stock prices (F), real gold price (G), fragility (FRA). The contribution of various categories of shocks is also considered (Panel B), i.e. oil supply side shocks (SUP: reserves, net negative and positive production, refinery margins), oil market demand side shocks (oil consumption, inventories), macroeconomic shocks (MAC: labor demand and supply, aggregate demand, fiscal stance, US fiscal and trade deficits, core inflation and productivity), financial shocks (FIN: excess liquidity, risk-free rate, term spread, housing prices, risk aversion, size, value, momentum, stock liquidity, leverage and factors, real oil price and nominal oil price volatility, real non-energy commodity prices, real stock prices, real gold prices), macro-financial shocks (MF: MAC+FIN), US$ exchange rate index shocks (X), oil futures market speculative shocks (SPC: Working-T index, futures basis), fragility factor own shock (FRA).

Table 2: Historical decomposition of the US financial fragility index: contribution of various categories of shocks in selected episodes

	Panel A: categories of shocks									**Panel B: sub categories of macroeconomic and financial shocks**							
	SUP	**DEM**	**MAC**	**X**	**FIN**	**SPC**	**OWN**	**MF**	**ACT**	**LM**	**Y**	**FT**	**N**	**W**	**MP**	**PA**	**RF**
87(4)	0.04	0.01	-0.05	-0.02	0.30	0.07	0.02	0.25	**0.36**	-0.03	-0.03	0.02	-0.01	0.00	0.05	0.01	0.24
90(4)	0.16	0.07	-0.02	-0.03	0.01	0.06	0.03	-0.01	**0.28**	0.05	0.03	-0.08	-0.03	0.00	0.02	0.03	-0.04
98(4)	0.02	-0.02	-0.08	0.00	0.26	0.01	0.09	0.18	**0.27**	-0.04	-0.13	0.07	-0.01	0.03	0.03	0.01	0.23
00(2)	0.01	-0.01	0.03	-0.01	0.25	0.00	0.04	0.28	**0.31**	-0.02	0.06	-0.10	0.00	0.09	0.01	0.08	0.16
07(3)	0.07	-0.01	-0.04	0.04	0.14	0.06	-0.03	0.09	**0.22**	0.02	0.00	0.02	-0.02	-0.06	-0.06	0.07	0.13
07(4)	0.07	0.00	0.03	0.00	0.08	0.01	0.01	0.12	**0.21**	0.04	-0.05	0.05	0.00	-0.02	0.04	0.00	0.04
08(1)	-0.02	-0.02	0.08	0.02	-0.06	-0.04	-0.01	0.02	-0.04	-0.01	0.01	0.04	-0.03	0.06	0.07	-0.17	0.04
08(2)	-0.03	-0.01	-0.02	-0.01	0.11	-0.02	0.01	0.08	0.03	-0.01	0.03	-0.09	0.02	0.03	0.11	-0.06	0.06
08(3)	0.04	0.00	0.28	0.01	0.00	-0.02	-0.03	0.28	**0.27**	0.03	0.03	0.10	0.02	0.10	0.01	0.05	-0.06
08(4)	0.03	0.06	0.49	0.03	0.35	0.04	0.03	0.84	**1.02**	0.16	0.08	0.14	0.01	0.10	0.02	0.10	0.24
09(1)	-0.03	-0.04	-0.09	-0.04	-0.37	-0.01	-0.05	-0.47	**-0.64**	-0.03	0.01	-0.05	0.01	-0.02	-0.05	-0.09	-0.23
09(2)	-0.08	-0.02	-0.22	-0.04	-0.15	-0.02	-0.01	-0.37	**-0.53**	-0.04	-0.08	-0.09	0.03	-0.04	-0.12	-0.02	-0.01
09(3)	-0.02	-0.01	-0.33	-0.02	-0.19	0.01	-0.01	-0.52	**-0.57**	-0.16	-0.04	-0.06	0.01	-0.08	0.03	-0.06	-0.17
09(4)	-0.05	0.02	-0.17	-0.03	0.07	-0.03	-0.01	-0.10	**-0.19**	-0.08	-0.01	-0.04	-0.01	-0.03	-0.01	0.04	0.04
10(1)	0.01	0.01	-0.13	0.04	-0.07	0.01	0.00	-0.19	**-0.13**	-0.09	0.03	-0.06	-0.01	0.00	0.03	-0.02	-0.07
10(2)	0.07	-0.06	0.12	-0.01	0.08	-0.02	-0.01	0.19	0.16	-0.01	0.05	0.10	0.03	-0.07	0.04	-0.02	0.06
10(3)	0.02	-0.01	0.14	0.00	-0.14	-0.04	0.08	-0.01	0.03	0.04	0.02	0.04	-0.01	0.05	0.02	-0.04	-0.12

The table reports the historical decomposition (net of base prediction) for the fragility index in differences, in selected episodes over the period 1986-2010, showing the contribution of subsets of structural shocks. In Panel A structural disturbances are aggregated in the following categories: oil supply (SUP, reserves, net production changes, refinery margins), oil demand (DEM: oil consumption, inventories), macroeconomic variables (MAC: labor demand and supply, aggregate demand, fiscal stance, US fiscal deficit, US trade deficit, core inflation, productivity), US$ exchange rate index (X), financial variables (FIN: excess liquidity, risk-free rate, term spread, real housing prices; risk aversion, size, value, momentum, stocks' liquidity and leverage factors; real commodity prices, real stock prices, real oil price and nominal oil price volatility), macro-finance shocks (MF: MAC+FIN), excess speculation in the oil futures market (SPC: Working-T index, futures basis), the own fragility shock (OWN); finally, ACT denotes actual changes in the fragility index. In Panel B, the contribution of macroeconomic and financial shocks is reported with reference to sub-categories of shocks, i.e. labor market shocks (LM: labor demand and supply), aggregate demand shocks (Y), deficits shocks (fiscal stance, US fiscal and trade deficits), core inflation shocks (N), productivity shocks (W), liquidity and interest rates shocks (MP: excess liquidity, risk-free rate, term spread), portfolio allocation shocks (PA: real housing prices, real non-energy commodity prices, real stock prices, real gold price, real oil price) and risk factors shocks (RF: nominal oil price volatility, risk aversion, size, value, momentum, stocks' liquidity and leverage factors).

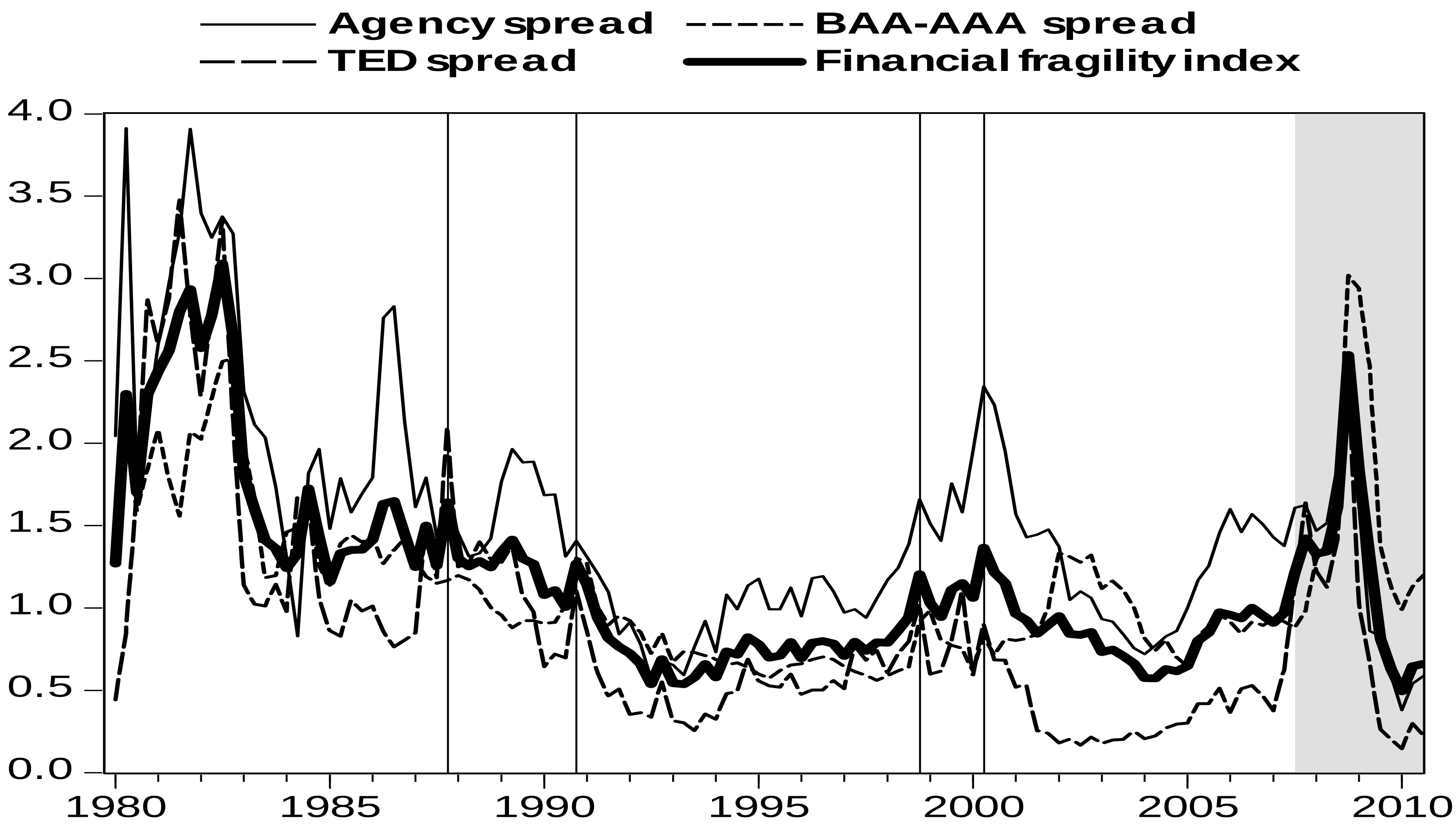

Figure 1: The AGENCY, TED and BAA-AAA spread, and the US financial fragility index (1980-2010).

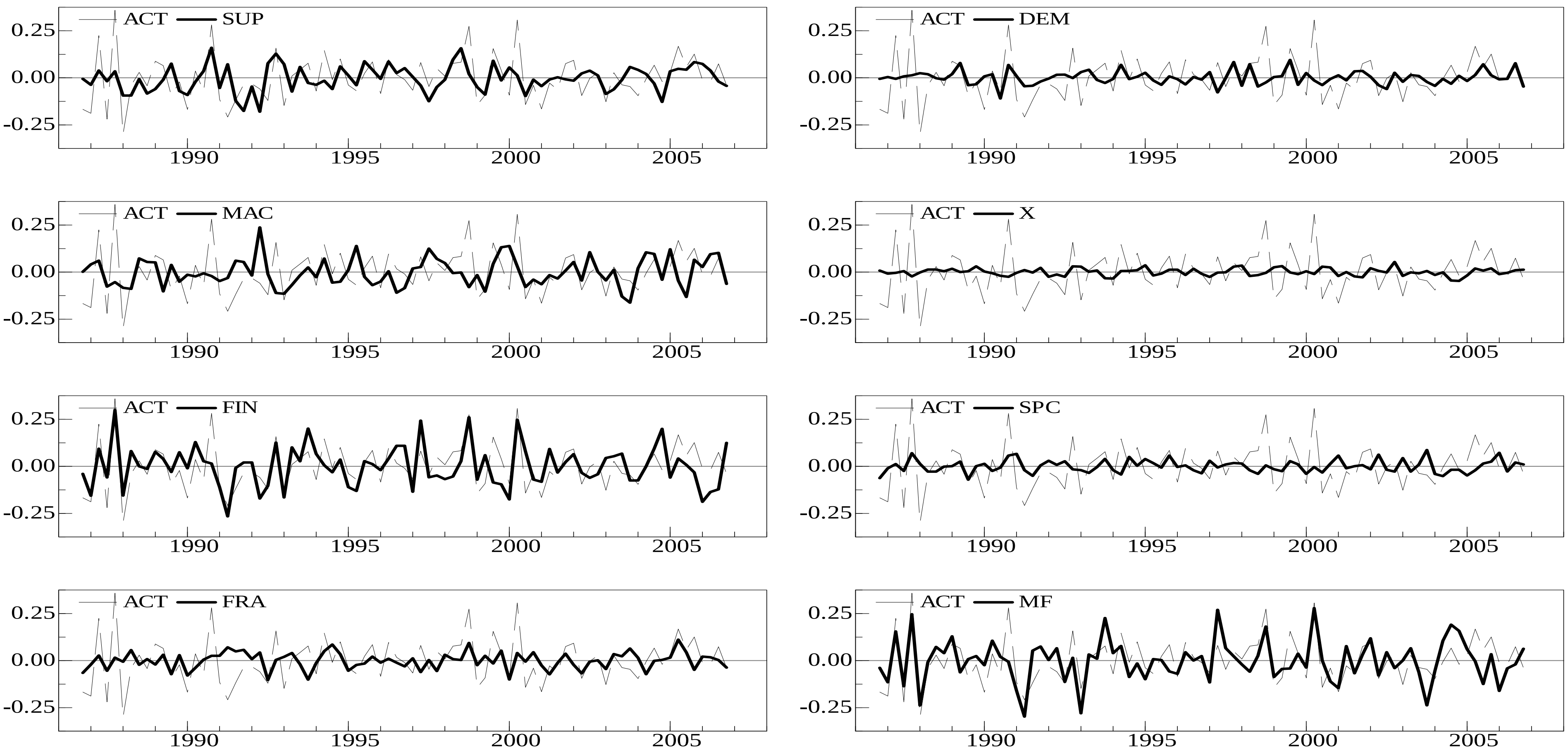

Figure 2: Historical decomposition for quarterly changes in the fragility index (ACT, dashed line); 1986:4-2006:4. Contributions from the oil market supply side shocks (SUP: reserves, net negative and positive production, refinery margins), oil market demand shocks (oil consumption, inventories), macroeconomic shocks (MAC: labor demand and supply, aggregate demand, fiscal stance, US fiscal and trade deficits, core inflation and productivity), financial shocks (FIN: excess liquidity, risk-free rate, term spread, housing prices; risk aversion, size, value, momentum, stocks' liquidity and leverage factors; real oil price and nominal oil price volatility, real non-energy commodity prices, real stock prices, real gold prices), macro-financial shocks (MF: MAC+FIN), US$ exchange rate index shocks (X), oil futures market speculative shocks (SPC: Working-T index, futures basis), fragility factor own shock (FRA).

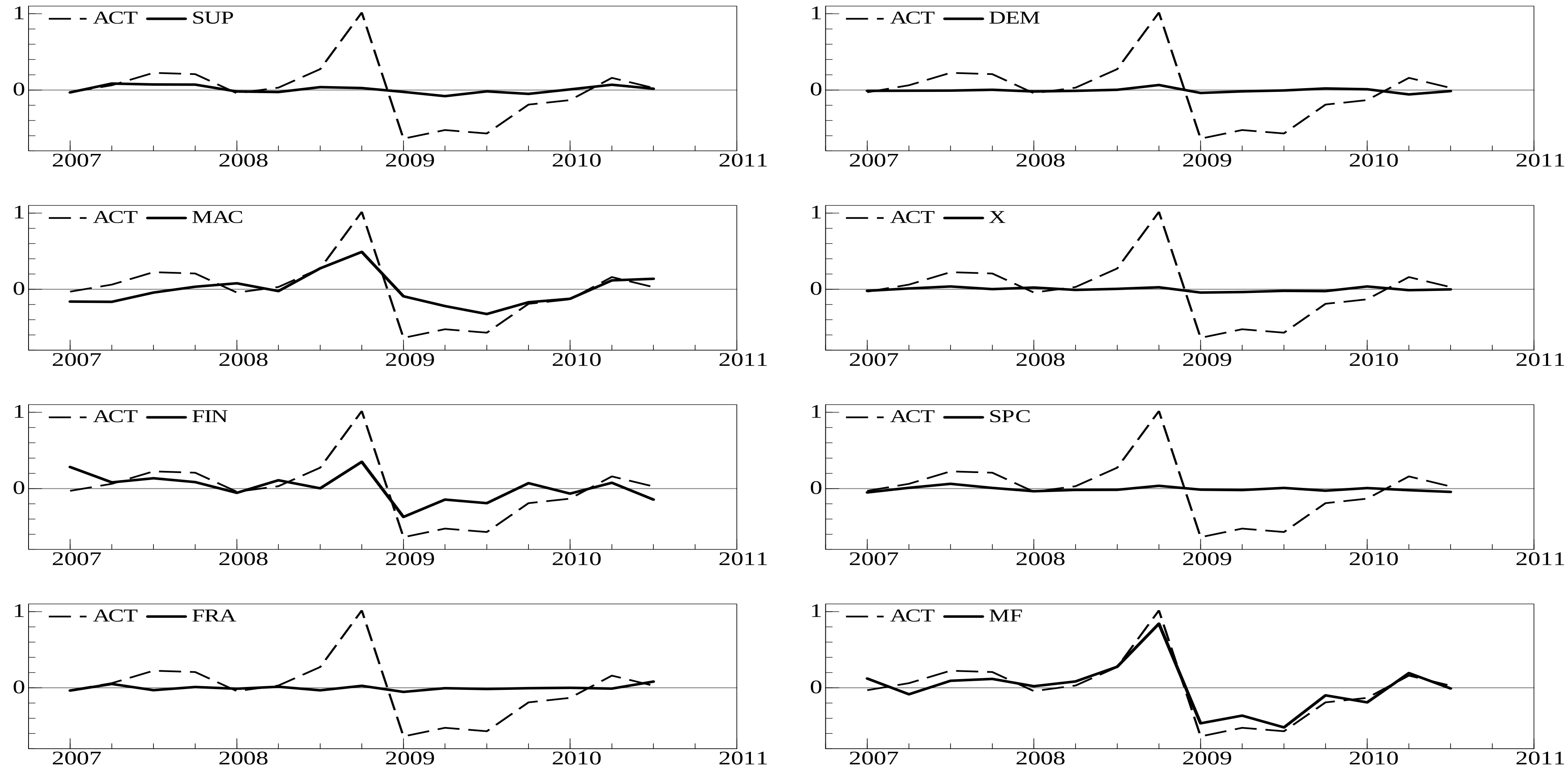

Figure 3: Historical decomposition for quarterly changes in the fragility index (ACT, dashed line); 2007:1-2010:3. Contributions from the oil market supply side shocks (SUP: reserves, net negative and positive production, refinery margins), oil market demand shocks (oil consumption, inventories), macroeconomic shocks (MAC: labor demand and supply, aggregate demand, fiscal stance, US fiscal and trade deficits, core inflation and productivity), financial shocks (FIN: excess liquidity, risk-free rate, term spread, housing prices; risk aversion, size, value, momentum, stocks' liquidity and leverage factors; real oil price and nominal oil price volatility, real non-energy commodity prices, real stock prices, real gold prices), macro-financial shocks (MF: MAC+FIN), US$ exchange rate index shocks (X), oil futures market speculative shocks (SPC: Working-T index, futures basis), fragility factor own shock (FRA).

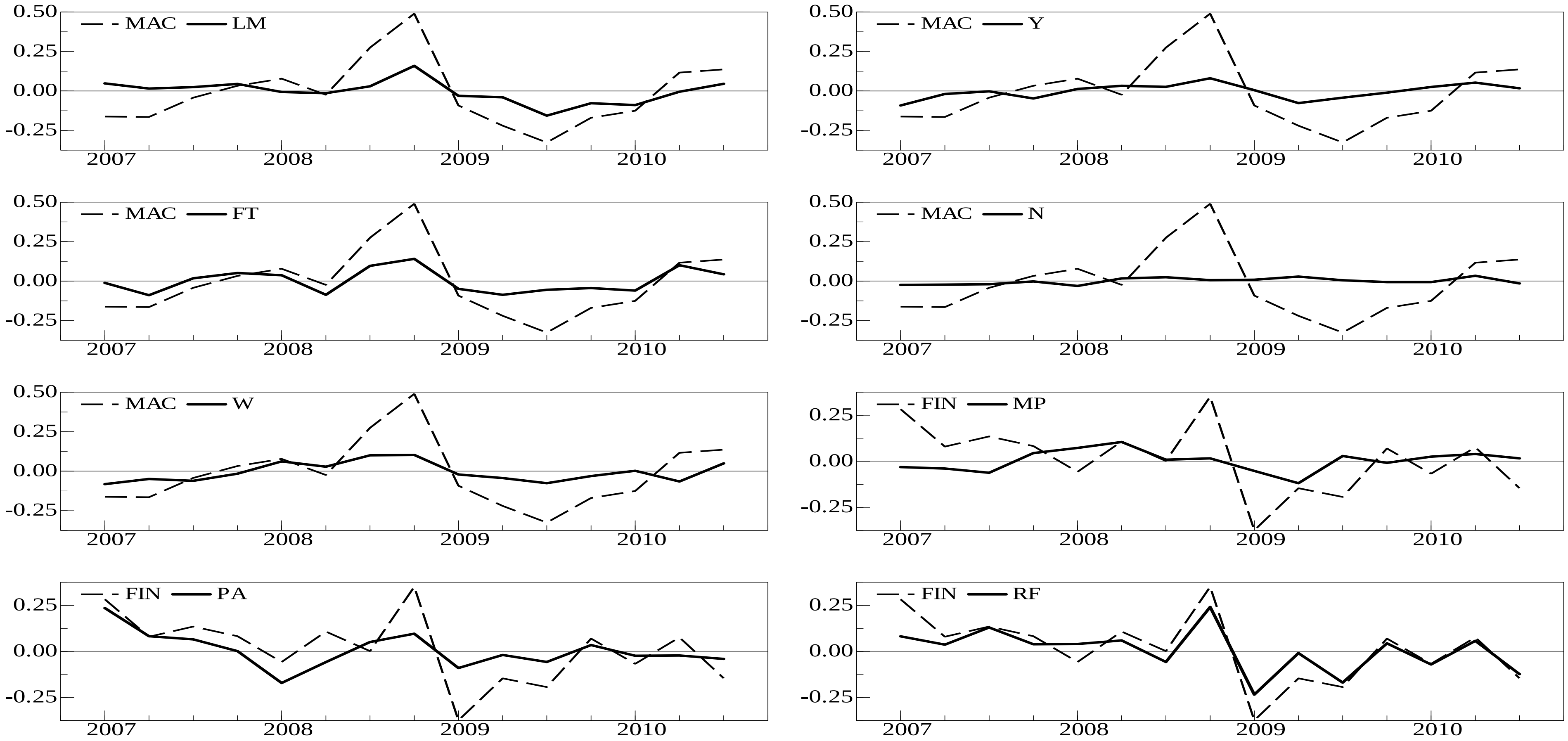

Figure 4: Historical decomposition for quarterly changes in the fragility index, 2007:1-2010:3. Contributions from the oil market supply side shocks (SUP: reserves, net negative and positive production, refinery margins), oil market demand shocks (oil consumption, inventories), macroeconomic shocks (MAC: labor demand and supply, aggregate demand, fiscal stance, US fiscal and trade deficits, core inflation and productivity), financial shocks (FIN: excess liquidity, risk-free rate, term spread, housing prices; risk aversion, size, value, momentum, stock liquidity and leverage factors; real oil price and nominal oil price volatility, real non-energy commodity prices, real stock prices, real gold prices), macro-financial shocks (MF: MAC+FIN), US$ exchange rate index shocks (X), oil market speculative shocks (SPC: Working-T index, futures basis), fragility factor own shock (FRA).

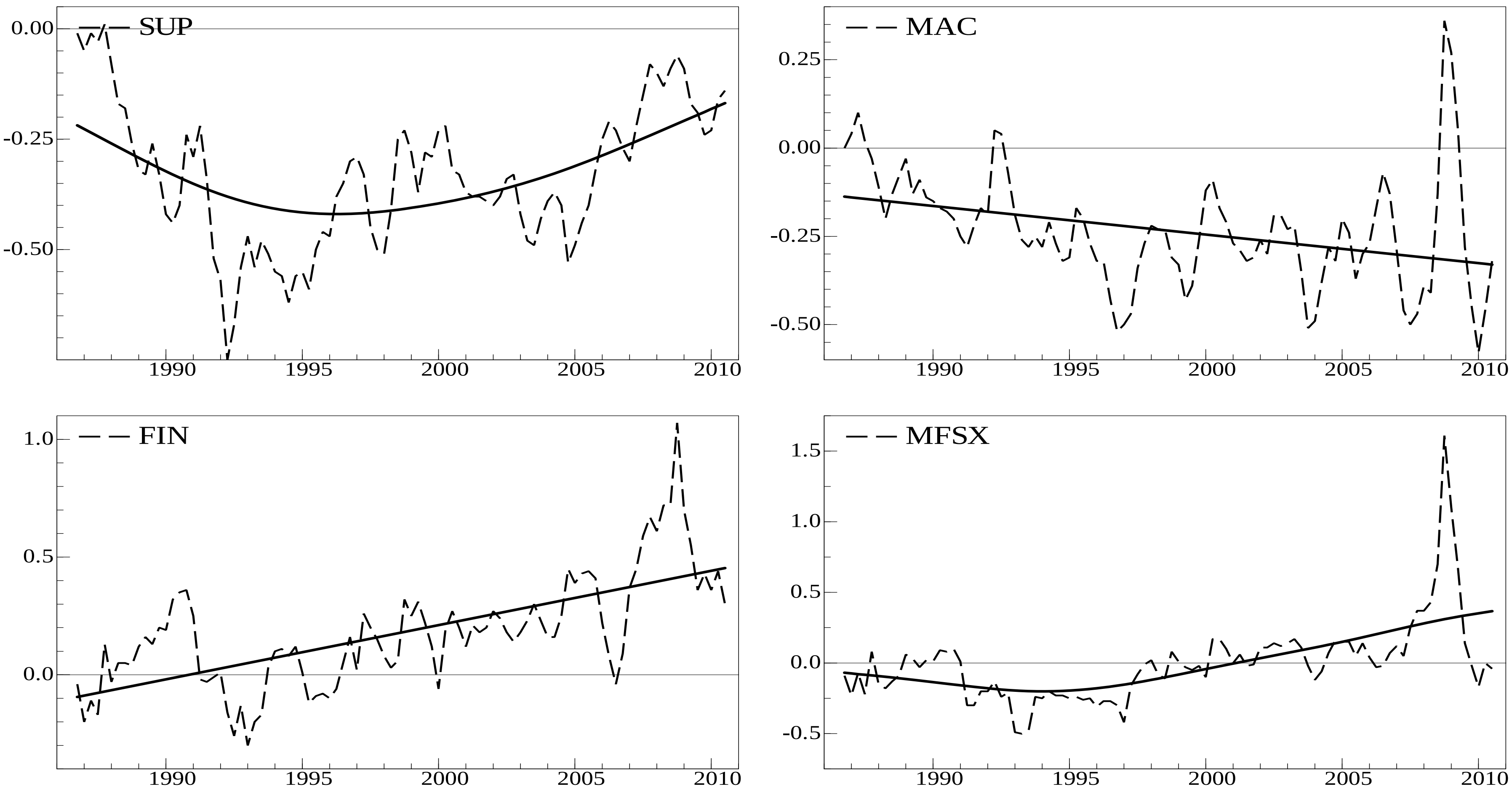

Figure 5: Historical decomposition of the fragility index (dashed line) with spline smoother (solid line); 1986:4-2010:3. Cumulative contributions from the oil market supply side shocks (SUP: reserves, net negative and positive production, refinery margins), macroeconomic shocks (MAC: labor demand and supply, aggregate demand, fiscal stance, US fiscal and trade deficits, core inflation and productivity), financial shocks (FIN: excess liquidity, risk-free rate, term spread, housing prices; risk aversion, size, value, momentum, stocks' liquidity and leverage factors; real oil price and nominal oil price volatility, real non-energy commodity prices, real stock prices, real gold prices), macro-financial shocks (MFSX: MAC+FIN+SPC+X; US$ exchange rate index shocks (X), oil market speculative shocks (SPC: Working-T index, futures basis).

Appendix for referee use only

7 Appendix 1: Econometric methodology

The econometric model is described by two blocks of equations. The former refers to the *observed* ($\mathbf{F}_{2,t}$) and *unobserved* ($\mathbf{F}_{1,t}$) global macro-financial factors and oil market demand and supply side variables ($\mathbf{O}_t$), collected in the $r\times1$ vector $\mathbf{F}_t = \left[\mathbf{F}_{1,t}' \ \mathbf{F}_{2,t}' \ \mathbf{O}_t'\right]'$, while the latter to q macro-financial variables for m countries ($n = m \times q$ equations in total). The joint dynamics of the "global" macro-finance-oil market interface (the global economy thereafter) and the "local" macro-finance interface are then modelled by means of the following reduced form dynamic factor model

$$
\begin{aligned}
(\mathbf{I} - \mathbf{P}(L))\mathbf{F}_t - \boldsymbol{\kappa}_t &= \boldsymbol{\eta}_t & (7)\\
\boldsymbol{\eta}_t &\sim i.i.d.(\mathbf{0}, \boldsymbol{\Sigma}_\eta) & (8)\\
(\mathbf{I} - \mathbf{C}(L))\left((\mathbf{Z}_t - \boldsymbol{\mu}_t) - \boldsymbol{\Lambda}\left(\mathbf{F}_t - \boldsymbol{\kappa}_t\right)\right) &= \mathbf{v}_t & (9)\\
\mathbf{v}_t &\sim i.i.d.(\mathbf{0}, \boldsymbol{\Sigma}_v). & (10)
\end{aligned}
$$

The model is cast in a weakly stationary representation, as $(\mathbf{F}_t - \boldsymbol{\kappa}_t), (\mathbf{Z}_t - \boldsymbol{\mu}_t) \sim I(0)$, where $\boldsymbol{\mu}_t$ and $\boldsymbol{\kappa}_t$ are $n \times 1$ and $r \times 1$ vectors of deterministic components, respectively, with $r \leq n$, including an intercept term, and, possibly, linear or non linear trends components.

Global dynamics are described by the stationary finite order polynomial matrix in the lag operator $\mathbf{P}(L)$, $\mathbf{P}(L) \equiv \mathbf{P}_1 L + \mathbf{P}_2 L^2 + ... + \mathbf{P}_p L^p$, where $\mathbf{P}_j$, $j = 1, .., p$, is a square matrix of coefficients of order r, and $\boldsymbol{\eta}_t$ is a $r \times 1$ vector of i.i.d. reduced form shocks driving the $\mathbf{F}_t$ factors. The contemporaneous effects of the global factors on each country variables in $\mathbf{Z}_t$ are measured by the loading coefficients collected in the $n \times r$ matrix $\boldsymbol{\Lambda} = \left[\boldsymbol{\Lambda}_{F_1}' \ \boldsymbol{\Lambda}_{F_2}' \ \boldsymbol{\Lambda}_O'\right]'$. Finally, $\mathbf{C}(L)$ is a finite order stationary block (own country) diagonal polynomial matrix in the lag operator, $\mathbf{C}(L) \equiv \mathbf{C}_1 L + \mathbf{C}_2 L^2 + ... + \mathbf{C}_c L^c$, where $\mathbf{C}_j$, $j = 1, .., c$, is a square matrix of coefficients of order n, partitioned as

$$
\underset{n\times n}{\mathbf{C}_j} = \begin{bmatrix} \underset{q\times q}{\mathbf{C}_{j,11}} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \underset{q\times q}{\mathbf{C}_{j,22}} & \cdots & \mathbf{0} \\ \vdots & \cdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \underset{q\times q}{\mathbf{C}_{j,mm}} \end{bmatrix}, \qquad (11)
$$

and $\mathbf{v}_t$ is the $n \times 1$ vector of i.i.d. reduced-form idiosyncratic (i.e. country-specific) disturbances. It is assumed that $E\left[\eta_{jt} v_{is}\right] = 0$ for all i, j, t, s.

The specification of the model in (7)-(9) embeds a set of important assumptions on the structure of global and local linkages: (i) global shocks ($\boldsymbol{\eta}_t$) affect both the global and local economy through the polynomial matrix $\mathbf{P}(L)$ and the factor loading matrix $\boldsymbol{\Lambda}$; (ii) idiosyncratic disturbances ($\mathbf{v}_t$) do not affect the global economy, while impact on the local economy only through own-country linkages ($\mathbf{C}(L)$ is block (own country) diagonal).

By substituting (7) into (9), the reduced form vector autoregressive (VAR) representation of the dynamic factor model can be written as

$$(\mathbf{I} - \mathbf{A}(L))(\mathbf{Y}_t - \boldsymbol{\gamma}_t) = \boldsymbol{\varepsilon}_t \tag{12}$$

where $\mathbf{Y}_t = [\mathbf{F}_t' \ \mathbf{Z}_t']'$, $\boldsymbol{\gamma}_t = [\boldsymbol{\kappa}_t' \ \boldsymbol{\mu}_t']'$,

$$\mathbf{A}(L) = \begin{pmatrix} \mathbf{P}(L) & \mathbf{0} \\ [\boldsymbol{\Lambda}\mathbf{P}(L) - \mathbf{C}(L)\boldsymbol{\Lambda}] & \mathbf{C}(L) \end{pmatrix},$$

$$\boldsymbol{\varepsilon}_t \equiv \begin{bmatrix} \boldsymbol{\varepsilon}_{1,t} \\ \boldsymbol{\varepsilon}_{2,t} \end{bmatrix} = \begin{bmatrix} \mathbf{I} \\ \boldsymbol{\Lambda} \end{bmatrix} [\boldsymbol{\eta}_t] + \begin{bmatrix} \mathbf{0} \\ \mathbf{v}_t \end{bmatrix},$$

with variance-covariance matrix

$$E[\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'] = \boldsymbol{\Sigma}_\varepsilon = \begin{pmatrix} \boldsymbol{\Sigma}_\eta & \boldsymbol{\Sigma}_\eta \boldsymbol{\Lambda}' \\ \boldsymbol{\Lambda}\boldsymbol{\Sigma}_\eta & \boldsymbol{\Lambda}\boldsymbol{\Sigma}_\eta\boldsymbol{\Lambda}' + \boldsymbol{\Sigma}_v \end{pmatrix},$$

where $E[\boldsymbol{\eta}_t \boldsymbol{\eta}_t'] = \boldsymbol{\Sigma}_\eta$ and $E[\mathbf{v}_t \mathbf{v}_t'] = \boldsymbol{\Sigma}_v$.

7.1 Estimation

Consistent and asymptotically Normal estimation of the model can be achieved following the multi-step iterative procedure described in Morana (2011a), which, for the current application, consists of the following steps.

• **Step 1: initialization.**

An initial estimate of the r_1 unobserved common factors in $\mathbf{F}_{1,t}$ can be obtained through the application of Principal Components Analysis (PCA) to the whole cross-country macro-financial data set $\mathbf{Z} = \{\mathbf{Z}_1, ..., \mathbf{Z}_T\}$ or, to enhance economic interpretability, on subsets of homogeneous cross-country data $\mathbf{Z}_i = \{\mathbf{Z}_{i,1}, ..., \mathbf{Z}_{i,T}\}$, $i = 1, ..., r_1$, $r_1 \leq q$; for instance, a GDP growth global factor can be estimated by means of the application of PCA to the vector of cross-country GDP growth data, a stock return global factor can be estimated through PCA applied to the vector of cross-country stock return data, and so on.

Then, conditional on the estimate of the unobserved stochastic factors, a preliminary estimate of the polynomial matrix $\mathbf{C}(L)$ and the factor loading matrix $\mathbf{\Lambda}$ is obtained by means of OLS estimation of the equation system in (9). This can be performed by first regressing $\hat{\mathbf{F}}_t$ on $\boldsymbol{\kappa}_t$ to obtain $\hat{\boldsymbol{\kappa}}_t$; then the actual series $\mathbf{Z}_t$ are regressed on $\boldsymbol{\mu}_t$ and $\hat{\mathbf{F}}_t - \hat{\boldsymbol{\kappa}}_t$ to obtain $\hat{\mathbf{\Lambda}}$ and $\hat{\boldsymbol{\mu}}_t$; $\hat{\mathbf{C}}(L)$ is then obtained by means of OLS estimation of the VAR model for the gap variables $\mathbf{Z}_t - \hat{\boldsymbol{\mu}}_t - \hat{\mathbf{\Lambda}}\left(\hat{\mathbf{F}}_t - \hat{\boldsymbol{\kappa}}_t\right)$ in (9).

• **Step 2: the iterative procedure.**

Next, a new estimate of the unobserved common factors in $\mathbf{F}_{1,t}$ can be obtained by means of PCA applied to the filtered variables $\mathbf{Z}_t^* = \mathbf{Z}_t - \left[\mathbf{I} - \hat{\mathbf{C}}(L)\right]\hat{\mathbf{\Lambda}}_*\left(\hat{\mathbf{F}}_{*,t} - \hat{\boldsymbol{\kappa}}_{*,t}\right)$, with $\hat{\mathbf{F}}_{*,t} = \left[\mathbf{F}_{2,t}' \ \mathbf{O}_t'\right]'$, $\hat{\mathbf{\Lambda}}_* = \left[\hat{\mathbf{\Lambda}}_{F_2}' \ \hat{\mathbf{\Lambda}}_O'\right]'$ and $\hat{\boldsymbol{\kappa}}_{*,t} = \left[\hat{\boldsymbol{\kappa}}_{F_2,t}' \ \hat{\boldsymbol{\kappa}}_{O,t}'\right]'$. Then, conditional on the new unobserved common factors, a new estimate of the polynomial matrix $\mathbf{C}(L)$ and the factor loading matrix $\mathbf{\Lambda}$ is attained as above described. The procedure is then iterated until convergence. Note that the proposed iterative procedure bears the interpretation of QML estimation performed by means of the EM algorithm. In the E-step the unobserved factors are estimated, given the observed data and the current estimate of model parameters, by means of PCA; in the M-step the likelihood function is maximized (OLS estimation of the $C(L)$ matrix is performed) under the assumption that the unobserved factors are known, conditioning on their E-step estimate. Convergence to the one-step QML estimate is ensured, as the value of the likelihood function is increased at each step. See Morana (2011a) for additional details on the asymptotic properties of the iterative estimation procedure.

• **Step 3: restricted estimation of the reduced form VAR model.** Once the final estimates of the unobserved factors $\mathbf{F}_{1,t}$ are available the polynomial matrix $\mathbf{P}(L)$ in (12) can be consistently estimated by various approaches, i.e. OLS estimation of an asymmetric or asymmetric VAR model, or of a symmetric restricted VAR (PC-VAR), as proposed and implemented in the current paper; then, by employing $\hat{\mathbf{P}}(L)$ and the final estimate of the $\mathbf{C}(L)$ and $\mathbf{\Lambda}$ matrices, the $\mathbf{\Phi}^*(L)$ polynomial matrix is estimated as $\hat{\mathbf{\Phi}}^*(L) = \left[\hat{\mathbf{\Lambda}}\hat{\mathbf{P}}(L) - \hat{\mathbf{C}}(L)\hat{\mathbf{\Lambda}}\right]$.

7.1.1 PC-VAR estimation

PC-VAR estimation of $\mathbf{P}(L)$ relies on a second round implementation of PCA on the global variables $\hat{\mathbf{F}}_t$. The rationale for the second-round application of PCA is different from the one justifying the first-round one. While the aim of the first-round application of PCA is estimating the unobserved global factors, the second round application aims at a parsimonious description of the information contained in the estimated ($\mathbf{F}_{1,t}$) and observed ($\mathbf{F}_{2,t}$, $\mathbf{O}_t$)

global factors, in order to lessen the curse of dimensionality affecting symmetric VAR models, in samples with temporal dimension typically available in applications using quarterly data.

Then, following Morana (2011c), given the $r \times 1$ vector $\mathbf{x}_t \equiv \hat{\mathbf{F}}_t - \hat{\boldsymbol{\kappa}}_t$, consider the vector autoregressive (VAR) model in (7).

PC-VAR estimation relies on the following identity

$$\mathbf{x}_t \equiv \hat{\boldsymbol{\Xi}}\hat{\mathbf{f}}_t, \tag{13}$$

where $\hat{\mathbf{f}}_t = \hat{\boldsymbol{\Xi}}'\mathbf{x}_t$ is the $r \times 1$ vector of estimated principal components of $\mathbf{x}_t$, $\hat{\boldsymbol{\Xi}}$ is the $r \times r$ matrix of orthogonal eigenvectors associated with the r (ordered) eigenvalues of $\hat{\boldsymbol{\Sigma}}$ ($\boldsymbol{\Sigma} = E\left[\mathbf{x}_t\mathbf{x}_t'\right]$). This follows from the eigenvalue-eigenvector decomposition of $\hat{\boldsymbol{\Sigma}}$, i.e. $\hat{\boldsymbol{\Xi}}^{-1}\hat{\boldsymbol{\Sigma}}\hat{\boldsymbol{\Xi}} = \hat{\boldsymbol{\Gamma}}$, where $\hat{\boldsymbol{\Gamma}} = diag(\hat{\gamma}_1, ..., \hat{\gamma}_r)$ is the $r \times r$ diagonal matrix containing the (ordered) eigenvalues of $\hat{\boldsymbol{\Sigma}}$.

PC-VAR estimation of $\mathbf{P}(L)$ would then be implemented as follows:

• apply PCA to $\mathbf{x}_t$ and compute $\hat{\mathbf{f}}_t = \hat{\boldsymbol{\Xi}}'\mathbf{x}_t$;

• obtain $\hat{\mathbf{D}}(L)$ by means of OLS estimation of the stationary dynamic vector regression model

$$\begin{aligned} \mathbf{x}_t &= \mathbf{D}(L)\hat{\mathbf{f}}_t + \boldsymbol{\varepsilon}_t \\ \boldsymbol{\varepsilon}_t &\sim i.i.d.\left(\mathbf{0}, \boldsymbol{\Sigma}_\varepsilon\right), \end{aligned} \tag{14}$$

where $\mathbf{D}(L) \equiv \mathbf{D}_1 L + \mathbf{D}_2 L^2 + ... + \mathbf{D}_p L^p$ features all the roots outside the unit circle;

• recover the (implied OLS) estimate of the actual parameters yield by the symmetric VAR model in (7) by solving the linear constraints

$$\hat{\mathbf{P}}(L)_{PCVAR} = \hat{\mathbf{D}}(L)\hat{\boldsymbol{\Xi}}'.$$

Note that, by construction, the PC-VAR estimator and the OLS estimator of the symmetric VAR model in (7) are the same estimator, i.e.

$$\hat{\mathbf{P}}(L)_{OLS} = \hat{\mathbf{P}}(L)_{PCVAR}.$$

In fact, substituting (13) in (7) yields

$$\mathbf{x}_t = \mathbf{P}(L)\hat{\boldsymbol{\Xi}}\hat{\mathbf{f}}_t + \boldsymbol{\eta}_t \tag{15}$$

i.e. the dynamic vector regression in (14), with $\mathbf{D}(L) = \mathbf{P}(L)\hat{\boldsymbol{\Xi}}$ and $\boldsymbol{\eta}_t = \boldsymbol{\varepsilon}_t$.

The implied $\mathbf{P}(L)$ matrix is then estimated by computing

$$\hat{\mathbf{D}}(L)\hat{\boldsymbol{\Xi}}' = \hat{\mathbf{P}}(L)\hat{\boldsymbol{\Xi}}\hat{\boldsymbol{\Xi}}' = \hat{\mathbf{P}}(L),$$

as $\hat{\boldsymbol{\Xi}}\hat{\boldsymbol{\Xi}}' = \mathbf{I}_r$ due to the orthonormality of the eigenvectors. The PC-VAR estimator would therefore show the same asymptotic properties of the OLS estimator.

The case considered is however of no interest for empirical implementations, as it does not allow for any dimensionality reduction, relatively to the estimation of the symmetric VAR model.

The unfeasible case Consider the case in which only the first s, $s < r$, principal components associated with the s largest ordered eigenvalues of $\hat{\boldsymbol{\Sigma}}$ are considered, with $\hat{\gamma}_j = 0$, $j = s+1, ..., r$. The same results as obtained above ($s = r$, implicitly) would hold.

Rewrite the identity in (13) as

$$\begin{aligned} \mathbf{x}_t &= \hat{\boldsymbol{\Xi}}_s\hat{\mathbf{f}}_{s,t} + \hat{\boldsymbol{\Xi}}_{r-s}\hat{\mathbf{f}}_{r-s,t} && (16) \\ &= \mathbf{x}_{*,t} + \boldsymbol{\tau}_t \\ &= \mathbf{x}_{*,t} && (17) \end{aligned}$$

where $\underset{(r\times 1)}{\hat{\mathbf{f}}_t} = \begin{bmatrix} \underset{(1\times s)}{\hat{\mathbf{f}}'_{s,t}} & \underset{(1\times(r-s))}{\hat{\mathbf{f}}'_{r-s,t}} \end{bmatrix}'$, $\underset{(r\times r)}{\hat{\boldsymbol{\Xi}}} = \begin{bmatrix} \underset{(r\times s)}{\hat{\boldsymbol{\Xi}}_s} & \underset{(r\times r-s)}{\hat{\boldsymbol{\Xi}}_{r-s}} \end{bmatrix}$, $\mathbf{x}_{*,t} \equiv \hat{\boldsymbol{\Xi}}_s\hat{\mathbf{f}}_{s,t}$, $\boldsymbol{\tau}_t \equiv \hat{\boldsymbol{\Xi}}_{r-s}\hat{\mathbf{f}}_{r-s,t} = \mathbf{0}$ as $\hat{\mathbf{f}}_{r-s,t} = \mathbf{0}$.

Then, substituting (16) in (7) yields

$$\begin{aligned} \mathbf{x}_t &= \mathbf{P}(L)\left(\mathbf{x}_{*,t} + \boldsymbol{\tau}_t\right) + \boldsymbol{\eta}_t && (18) \\ &= \mathbf{P}(L)\mathbf{x}_{*,t} + \boldsymbol{\eta}_t. \end{aligned}$$

PC-VAR would then entail OLS estimation of

$$\begin{aligned} \mathbf{x}_t &= \mathbf{D}(L)\hat{\mathbf{f}}_{s,t} + \boldsymbol{\varepsilon}_t && (19) \\ \boldsymbol{\varepsilon}_t &\sim i.i.d.\left(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon}}\right). \end{aligned}$$

Then, by writing $\mathbf{D}_*(L) \equiv \mathbf{D}_{*1}L + \mathbf{D}_{*2}L^2 + ... + \mathbf{D}_{*p}L^p$, with $\mathbf{D}_{*j}(L) = \begin{bmatrix} \underset{(r\times s)}{\mathbf{D}_j(L)} & \underset{(r\times r-s)}{\mathbf{0}} \end{bmatrix}$, $j = 1, ..., p$, and $\mathbf{P}_*(L) \equiv \mathbf{P}_{1*}L + \mathbf{P}_{2*}L^2 + ... + \mathbf{P}_{p*}L^p$, with

$\mathbf{P}_{*j} = \begin{bmatrix} \underset{(r\times s)}{\mathbf{P}_j\hat{\boldsymbol{\Xi}}_s} & \underset{(r\times r-s)}{\mathbf{0}} \end{bmatrix} = \begin{bmatrix} \underset{(r\times r)}{\mathbf{P}_j} & \underset{(r\times r-s)}{\mathbf{0}} \end{bmatrix} \odot \hat{\boldsymbol{\Xi}}$, $j = 1, ..., p$, and where $\odot$ is the Hadamart product, it follows that

$$\begin{aligned} \hat{\mathbf{D}}_*(L)\hat{\boldsymbol{\Xi}}' &= \hat{\mathbf{P}}_*(L)\hat{\boldsymbol{\Xi}}' \\ &= \hat{\mathbf{P}}(L) \odot \hat{\boldsymbol{\Xi}}\ \hat{\boldsymbol{\Xi}}' \\ &= \hat{\mathbf{P}}(L), \end{aligned}$$

That is,

$$\hat{\mathbf{P}}(L)_{PCVAR} = \hat{\mathbf{D}}_*(L)\hat{\boldsymbol{\Xi}}' = \hat{\mathbf{D}}(L)\hat{\boldsymbol{\Xi}}_s'. \tag{20}$$

The feasible case Consider the case in which only the first s, $s < r$, principal components associated with the s largest ordered eigenvalues of $\hat{\boldsymbol{\Sigma}}$ are considered and $\gamma_j \simeq 0$, $j = s+1, ..., r$.

Consistency of the PC-VAR estimator in (20)

$$\hat{\mathbf{P}}(L)_{PCVAR} = \hat{\mathbf{D}}(L)\hat{\boldsymbol{\Xi}}_s',$$

obtained from OLS estimation of (19), can then be established.

In fact, by rewriting (18) as

$$\begin{aligned} \mathbf{x}_t &= \mathbf{P}(L)\mathbf{x}_{*,t} + \mathbf{P}(L)\boldsymbol{\tau}_t + \boldsymbol{\eta}_t & (21) \\ &= \mathbf{P}(L)\hat{\boldsymbol{\Xi}}_s\hat{\mathbf{f}}_{s,t} + \mathbf{P}(L)\hat{\boldsymbol{\Xi}}_{r-s}\hat{\mathbf{f}}_{r-s,t} + \boldsymbol{\eta}_t \\ &= \mathbf{P}(L)\hat{\boldsymbol{\Xi}}_s\hat{\mathbf{f}}_{s,t} + \boldsymbol{\vartheta}_t, & (22) \end{aligned}$$

where $\boldsymbol{\vartheta}_t = \boldsymbol{\eta}_t + \mathbf{P}(L)\boldsymbol{\tau}_t \simeq \boldsymbol{\eta}_t$, as, for $\gamma_j \to 0$, $\hat{\mathbf{f}}_{r-s,t} \to \mathbf{0}$.

Consistency of the PC-VAR estimator $\hat{\mathbf{D}}(L)\hat{\boldsymbol{\Xi}}_s'$ depends on the limiting contemporaneous uncorrelation condition $plim\left(\frac{\hat{\mathbf{f}}_s'\boldsymbol{\vartheta}}{T}\right) = \mathbf{0}$ being satisfied, where $\hat{\mathbf{f}}_s = \begin{bmatrix} \hat{\mathbf{f}}_{s,-1} & ... & \hat{\mathbf{f}}_{s,-p} \end{bmatrix}$ is the $T \times (s \times p)$ design matrix containing the temporal information on the lagged principal components and $\boldsymbol{\vartheta}$ is the $T \times 1$ vector containing the temporal information on the error process. The latter condition would necessarily hold for the $p = 1$ case, as $plim\left(\frac{\mathbf{x}_{*,t-1}\boldsymbol{\tau}_{t-1}}{T}\right) = \mathbf{0}$ by construction, due to the orthogonality of $\hat{\mathbf{f}}_{s,t}$ and $\hat{\mathbf{f}}_{r-s,t}$, and therefore of $\mathbf{x}_{*,t}$ and $\boldsymbol{\tau}_t$. For the $p > 1$ case, the condition $plim\left(\frac{\mathbf{x}_{*,t-i}\boldsymbol{\tau}_{t-j}}{T}\right) = \mathbf{0}$, $i, j = 1, ..., p$, $i \neq j$, would appear to be required. As under the weak stationarity assumption, for any generic element in the $\mathbf{x}_{*,t}$ and $\boldsymbol{\tau}_t$ vectors, the Wold decomposition would yield

$$\begin{aligned} x_{*m,t-i} &= \gamma(L)\varepsilon_{x_{*,m},t-i} \qquad m = 1, ..., s \\ \varepsilon_{x_{*,m},t} &\sim i.i.d.\left(0, \sigma^2_{\varepsilon_{x_{*,m}}}\right) \end{aligned}$$

$$\begin{aligned} \tau_{*n,t-j} &= \theta(L)\varepsilon_{\tau_n,t-j} \qquad n = 1, ..., r-s \\ \varepsilon_{\tau_n,t} &\sim i.i.d.\left(0, \sigma^2_{\tau_n}\right), \end{aligned}$$

with $\gamma(L)$ and $\theta(L)$ stationary infinite order polynomials in the lag operator, provided $E\left[\varepsilon_{x_{*,m},t}\varepsilon_{\tau_n,t}\right] = 0$, the necessary conditions for consistency would then be satisfied; the latter requirement it appears to be not restrictive. Asymptotic Normality also follows under the same conditions of validity for the OLS estimator.

Monte Carlo results (see the Appendix) strongly support the PC-VAR estimation strategy, showing that the suggested procedure may yield gains, in terms of both lower bias and higher efficiency, over unrestricted OLS VAR estimation. Selecting s such that the proportion of total variance accounted for by the extracted principal components is in the range 80% to 90% would be advisable for empirical applications in general.

7.1.2 Reduced form vector moving average representation of the F-VAR model

By inverting the VAR model in (12), the reduced form VMA representation is obtained; this yields

$$\mathbf{Y}_t - \boldsymbol{\gamma}_t = \mathbf{H}(L)\boldsymbol{\varepsilon}_t, \tag{23}$$

where $\mathbf{H}(L) \equiv (\mathbf{I} - \mathbf{A}(L))^{-1}$.

By partitioning $\mathbf{H}(L)$ according to the block diagonal structure of (12), i.e. $\mathbf{H}(L) \equiv \begin{pmatrix} \mathbf{H}_F(L) & \mathbf{0} \\ \mathbf{H}_{FZ}(L) & \mathbf{H}_Z(L) \end{pmatrix}$, the VMA representation in (23) can then be written

$$\begin{pmatrix} \mathbf{F}_t - \boldsymbol{\kappa}_t \\ \mathbf{Z}_t - \boldsymbol{\mu}_t \end{pmatrix} = \begin{pmatrix} \mathbf{H}_F(L) & \mathbf{0} \\ \mathbf{H}_{FZ}(L) & \mathbf{H}_Z(L) \end{pmatrix} \begin{pmatrix} \boldsymbol{\varepsilon}_{1,t} \\ \boldsymbol{\varepsilon}_{2,t} \end{pmatrix}. \tag{24}$$

7.1.3 Structural vector moving average representation of the F-VAR model

The identification of the structural shocks can be achieved through the following double-Choleski strategy.

Denoting by $\boldsymbol{\xi}_t$ the vector of the r structural shocks driving the common factors in $\mathbf{F}_t$, the relation between the reduced form and the structural factor disturbances can be written as $\boldsymbol{\xi}_t = \mathbf{K}\,\boldsymbol{\eta}_t$, where $\mathbf{K}$ is a $r \times r$ invertible matrix. By assumption the structural factor shocks are orthogonal and have unit variance, so that $E[\boldsymbol{\xi}_t\boldsymbol{\xi}_t'] = \mathbf{K}\,\boldsymbol{\Sigma}_\eta\,\mathbf{K}' = \mathbf{I}_r$. To achieve exact identification of the structural disturbances, additional $r(r-1)/2$ restrictions need to be imposed. Since $\boldsymbol{\eta}_t = \mathbf{K}^{-1}\boldsymbol{\xi}_t$, imposing exclusion restrictions on the contemporaneous impact matrix amounts to imposing zero restrictions on the elements of $\mathbf{K}^{-1}$, for which a lower-triangular structure is assumed. This latter assumption implies a precise "ordering" of the common factors in $\mathbf{F}_t$. In particular, the first factor is allowed to have a contemporaneous impact on all other factors, but reacts only with a one-period lag to the other structural disturbances; instead, the last factor is contemporaneously affected by all structural shocks, having only lagged effects on all other factors. Operationally, $\mathbf{K}^{-1}$ (with the $r(r-1)/2$ zero restrictions necessary for exact identification imposed) is estimated by the Choleski decomposition of the factor innovation variance-covariance matrix $\boldsymbol{\Sigma}_\eta$, i.e. $\hat{\mathbf{K}}^{-1} = chol(\hat{\boldsymbol{\Sigma}}_\eta)$.

A similar procedure is applied to obtain the identification of the idiosyncratic structural shocks driving the innovations in $\mathbf{v}_t$, which can be estimated by regressing $\hat{\varepsilon}_{2,t}$ on $\hat{\boldsymbol{\eta}}_t$ by OLS, yielding $\hat{\mathbf{v}}_t$ as the residuals. Denoting by $\boldsymbol{\upsilon}_t$ the vector of n structural idiosyncratic shocks (uncorrelated with the $\boldsymbol{\xi}_t$ shocks), the relation between the reduced form and the structural idiosyncratic disturbances can be written as $\boldsymbol{\upsilon}_t = \mathbf{G}\,\mathbf{v}_t$, where $\mathbf{G}$ is a $n \times n$ invertible matrix. In addition to the orthogonality conditions $E[\boldsymbol{\upsilon}_t\boldsymbol{\upsilon}_t'] = \mathbf{G}\boldsymbol{\Sigma}_v'\mathbf{G}' = \mathbf{I}_n$, $n(n-1)/2$ zero restrictions are needed for exact identification. Since $\mathbf{v}_t = \mathbf{G}^{-1}\boldsymbol{\upsilon}_t$, the required restrictions can be imposed by assuming a lower-triangular structure for the contemporaneous impact matrix $\mathbf{G}^{-1}$. Operationally, also $\mathbf{G}^{-1}$ is then estimated by the Choleski decomposition of the idiosyncratic innovation variance-covariance matrix $\boldsymbol{\Sigma}_v$, i.e. $\hat{\mathbf{G}}^{-1} = chol(\hat{\boldsymbol{\Sigma}}_v)$.

The structural VMA representation can then be written as

$$\begin{pmatrix} \mathbf{F}_t - \boldsymbol{\kappa}_t \\ \mathbf{Z}_t - \boldsymbol{\mu}_t \end{pmatrix} = \begin{pmatrix} \mathbf{H}_F(L)\mathbf{K}^{-1} & \mathbf{0} \\ \mathbf{H}_{FZ}(L)\mathbf{K}^{-1} & \mathbf{H}_Z(L)\mathbf{G}^{-1} \end{pmatrix} \begin{pmatrix} \boldsymbol{\xi}_t \\ \boldsymbol{\upsilon}_t \end{pmatrix}. \tag{25}$$

Forecast error variance and historical decompositions can then be obtained by means of standard formulas.

Following the thick modelling strategy of Granger and Jeon (2004), median estimates of the parameters of interest, impulse responses, forecast error variance and historical decompositions, as well as of their confidence intervals, robust to model misspecification, can be obtained by means of simulated implementation of the proposed estimation strategy.

PC-VAR: Monte Carlo results

Consider the following data generation process (DGP) for the $n \times 1$ vector process $\mathbf{x}_t$

$$
\begin{aligned}
\mathbf{\Phi}(L)\,\mathbf{x}_t &= \mathbf{v}_t \\
\mathbf{v}_t &\sim n.i.d.(\mathbf{0}, \mathbf{\Sigma}_v),
\end{aligned}
\tag{26}
$$

where $n = 25$, $\mathbf{\Phi}(L) = diag\begin{pmatrix} \phi_1(L) & \dots & \phi_n(L) \end{pmatrix}$, with

i) $\phi_i(L) = 1 - 0.4L$, $i = 1, ..., n$, for the first order case;

ii) $\phi_i(L) = 1 - 0.4L - 0.2L^2$, $i = 1, ..., n$, for the second order case;

iii) $\phi_i(L) = 1 - 0.4L - 0.2L^2 + 0.2L^3$, $i = 1, ..., n$, for the third order case;

iv) $\phi_i(L) = 1 - 0.4L - 0.2L^2 + 0.2L^3 - 0.1L^4$, $i = 1, ..., n$, for the fourth order case;

$$
\mathbf{\Sigma}_v = \begin{bmatrix} 1 & \rho & \cdots & \rho \\ \rho & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \rho \\ \rho & \cdots & \rho & 1 \end{bmatrix}, \text{ with } \rho = \{0, 0.3, 0.6, 0.9\}.
$$

The estimated models are the PC-VAR(p, r) model, considering r principal components, $r = 2, 4, ..., 24$ and $p = 1, .., 4$ lags, and the unrestricted VAR(p) model, equivalent to the PC-VAR(p, r) model with $r = n$ (25). The temporal (usable) sample size is $T = 100$ and the number of replications is 500.

The results of the Monte Carlo analysis are reported in Table A1. In the table results at the system level only, i.e the mean absolute bias and the root mean square error, across parameters and equations, are reported.

As is shown in Table A1, PC-VAR estimation does allow to improve over unrestricted OLS VAR estimation, in terms of both lower bias and higher efficiency, independently of the order of the system and the strength of the contemporaneous cross-sectional correlation relating the error terms. By following a bias minimization criterion, two broad cases may however be distinguished, i.e. the non-correlated errors case ($\rho = 0$) and the correlated errors case ($\rho \geq 0.3$). For the former one, the required proportion of total variance to be explained (optimal number of principal components) ranges between about 50% and 90%, depending on the order of the system, falling as the order of the system increases. On the other hand, a tighter required explained variance interval can be found for the latter case, increasing with the strength of the cross-sectional correlation: 80% to 90% for the low correlation case ($\rho = 0.3$), 85% to 95% for the intermediate correlation case ($\rho = 0.6$), and 90% to 100% for the high correlation case ($\rho = 0.9$). Moreover, also for the correlation case the required proportion of explained variance tends to fall as the order of the system increases.

Overall, while the bias improvement is small, yet sizable (10% to 20%) for the VAR(1) and VAR(2) cases, for which the degrees of freedom are not smaller than 50% of the sample size, PC-VAR estimation yields a much more dramatic bias reduction (60% to 80%) for the VAR(3) and VAR(4) cases, as the degrees of freedom fall to 25% of the sample size and 0, respectively. Similarly concerning efficiency, as PC-VAR yields a RMSE reduction in the range 30% to 50% for the VAR(1) and VAR(2) case, and 60% to 90% for the VAR(3) and VAR (4) case.

Table A1: Monte Carlo results.

	# PC (explained total variance)												
ρ=0	**2**(.18)	**4**(.32)	**6**(.44)	**8**(.55)	**10**(.64)	**12**(.72)	**14**(.78)	**16**(.84)	**18**(.89)	**20**(.93)	**22**(.96)	**24**(.99)	**25**(1.0)
	PC-VAR(1)												***VAR(1)***
Bias	0.015	0.014	0.013	0.012	0.011	0.010	0.009	0.009	0.008	0.008	0.008	0.008	0.009
RMSE	0.054	0.064	0.069	0.072	0.075	0.078	0.082	0.085	0.090	0.096	0.104	0.114	0.120
	PC-VAR(2)												***VAR(2)***
Bias	0.012	0.011	0.010	0.010	0.009	0.009	0.009	0.009	0.009	0.009	0.010	0.010	0.011
RMSE	0.046	0.056	0.063	0.069	0.074	0.080	0.087	0.094	0.103	0.114	0.126	0.142	0.151
	PC-VAR(3)												***VAR(3)***
Bias	0.011	0.010	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.010	0.011	0.013	0.014
RMSE	0.044	0.054	0.062	0.069	0.076	0.084	0.094	0.105	0.119	0.136	0.158	0.187	0.208
	PC-VAR(4)												***VAR(4)***
Bias	0.009	0.009	0.008	0.008	0.008	0.008	0.009	0.009	0.010	0.012	0.015	0.019	0.027
RMSE	0.040	0.051	0.060	0.069	0.078	0.089	0.102	0.119	0.142	0.175	0.229	0.334	0.515

	# PC (explained total variance)												
ρ=0.3	**2**(.40)	**4**(.51)	**6**(.60)	**8**(.68)	**10**(.74)	**12**(.80)	**14**(.85)	**16**(.89)	**18**(.92)	**20**(.95)	**22**(.97)	**24**(.99)	**25**(1.0)
	PC-VAR(1)												***VAR(1)***
Bias	0.028	0.024	0.021	0.018	0.015	0.013	0.011	0.010	0.009	0.009	0.009	0.009	0.010
RMSE	0.053	0.064	0.071	0.076	0.080	0.085	0.090	0.096	0.102	0.111	0.120	0.132	0.140
	PC-VAR(2)												***VAR(2)***
Bias	0.021	0.018	0.015	0.013	0.012	0.010	0.010	0.010	0.010	0.010	0.010	0.011	0.012
RMSE	0.045	0.058	0.067	0.075	0.082	0.090	0.098	0.108	0.119	0.132	0.147	0.165	0.177
	PC-VAR(3)												***VAR(3)***
Bias	0.019	0.016	0.014	0.012	0.011	0.010	0.010	0.010	0.010	0.011	0.012	0.014	0.015
RMSE	0.042	0.055	0.065	0.075	0.084	0.095	0.107	0.120	0.137	0.158	0.184	0.219	0.242
	PC-VAR(4)												***VAR(4)***
Bias	0.016	0.014	0.012	0.010	0.010	0.009	0.009	0.010	0.011	0.013	0.016	0.021	0.030
RMSE	0.038	0.053	0.064	0.075	0.087	0.101	0.117	0.137	0.164	0.203	0.265	0.392	0.598

	# PC (explained total variance)												
ρ=0.6	**2**(.65)	**4**(.72)	**6**(.77)	**8**(.81)	**10**(.85)	**12**(.89)	**14**(.91)	**16**(.94)	**18**(.96)	**20**(.97)	**22**(.99)	**24**(1.0)	**25**(1.0)
	PC-VAR(1)												***VAR(1)***
Bias	0.028	0.024	0.021	0.018	0.015	0.013	0.012	0.011	0.010	0.010	0.010	0.010	0.011
RMSE	0.055	0.069	0.079	0.086	0.094	0.102	0.111	0.120	0.130	0.143	0.157	0.173	0.183
	PC-VAR(2)												***VAR(2)***
Bias	0.021	0.018	0.016	0.013	0.012	0.011	0.010	0.010	0.010	0.011	0.012	0.013	0.014
RMSE	0.049	0.066	0.079	0.090	0.100	0.112	0.124	0.137	0.152	0.170	0.191	0.216	0.231
	PC-VAR(3)												***VAR(3)***
Bias	0.019	0.016	0.014	0.012	0.011	0.011	0.011	0.011	0.011	0.013	0.014	0.016	0.018
RMSE	0.046	0.064	0.078	0.092	0.105	0.119	0.136	0.155	0.178	0.205	0.240	0.286	0.319
	PC-VAR(4)												***VAR(4)***
Bias	0.016	0.014	0.012	0.011	0.010	0.010	0.011	0.012	0.013	0.015	0.018	0.026	0.035
RMSE	0.043	0.062	0.078	0.094	0.109	0.129	0.151	0.179	0.216	0.267	0.347	0.511	0.774

	# PC (explained total variance)												
ρ=0.9	**2**(.91)	**4**(.93)	**6**(.94)	**8**(.95)	**10**(.96)	**12**(.97)	**14**(.98)	**16**(.98)	**18**(.99)	**20**(.99)	**22**(1.0)	**24**(1.0)	**25**(1.0)
	PC-VAR(1)												***VAR(1)***
Bias	0.028	0.024	0.021	0.018	0.017	0.014	0.013	0.014	0.014	0.014	0.016	0.016	0.017
RMSE	0.065	0.094	0.116	0.137	0.157	0.177	0.200	0.224	0.252	0.279	0.309	0.344	0.366
	PC-VAR(2)												***VAR(2)***
Bias	0.021	0.018	0.016	0.015	0.014	0.014	0.014	0.014	0.015	0.018	0.019	0.021	0.023
RMSE	0.067	0.105	0.133	0.158	0.183	0.210	0.238	0.267	0.299	0.337	0.378	0.426	0.457
	PC-VAR(3)												***VAR(3)***
Bias	0.019	0.016	0.015	0.015	0.015	0.014	0.015	0.014	0.015	0.018	0.019	0.022	0.025
RMSE	0.067	0.104	0.134	0.163	0.193	0.225	0.262	0.302	0.348	0.404	0.472	0.564	0.623
	PC-VAR(4)												***VAR(4)***
Bias	0.016	0.014	0.013	0.013	0.013	0.014	0.015	0.017	0.020	0.024	0.029	0.045	0.055
RMSE	0.066	0.107	0.141	0.172	0.206	0.244	0.289	0.347	0.419	0.527	0.683	1.037	1.434

The Table reports Monte Carlo (absolute) bias and RMSE statistics (average across parameters and equations), from PC-VAR and unrestricted OLS VAR estimation, of first, second, third, and fourth order systems, with residuals correlation coefficient $\boldsymbol{\rho}$ = (0, 0.3, 0.6, 0.9), temporal sample size $\boldsymbol{T}$ = 100, sectional sample size $\boldsymbol{n}$ = 25, and 500 replications. The estimated models are the PC-VAR model, considering r principal components, r=2,4,...,24, and the unrestricted VAR model, equivalent to the PC-VAR model with r=n (25) principal components.

8 Appendix 2: interpretation of the structural shocks

Concerning physical oil market interactions, eight structural shocks can be identified, i.e. an *oil reserves* shock, *net positive* and *negative production* shocks, a *refinery margins* shock, *oil consumption* and *inventories preferences* shocks, and *other real oil price* and *nominal oil price volatility* shocks. Moreover, concerning macroeconomic dynamics, eight structural shocks can be identified, i.e. an *aggregate demand* shock, a *labor supply* shock, a (*negative*) labor demand shock, a *productivity* shock, *US fiscal* and *trade deficit* shocks, a (global) *fiscal stance* shock, and a *core inflation* shock. Finally, concerning financial dynamics, seventeen structural shocks can be identified, i.e. an *excess liquidity* shock; a set of *speculative asset price (portfolio)* shocks, i.e. a *real stock market prices* shock, a *real housing prices* shock, a *real gold price* shock and a *real non energy commodity price index* shock; an *US$ exchange rate index* shock; a *risk-free rate* shock; two oil futures market speculative shocks, i.e. *Working's-T* and *futures basis* shocks; a set of *risk factors* shocks, measuring revisions in market expectations about future fundamentals, i.e. a *risk aversion* shock, *size*, *value*, *leverage*, *stocks' liquidity*, and *momentum* factor shocks; a *term spread* shock; a *residual economic and financial fragility index* shock.

8.1 The oil market shocks

The interpretation of the own shocks in terms of reserves, net production and refinery margins shocks is clear-cut, the latter accounting for about 100% of each variable fluctuations at the impact (not reported). The interpretation of the oil consumption and inventories own shocks in terms of preferences shocks depends on the former being net of the contemporaneous effect of the macroeconomic variables driving flow oil demand, and the latter also of the effect of the (financial) variables driving financial oil demand. Similarly for the real oil price and nominal oil price volatility own shocks, to which we do not attach an economic interpretation and simply refer as *other* real oil price and nominal oil price volatility shocks.

8.2 The macroeconomic shocks

The aggregate demand (real activity) shock accounts for 80% of real activity fluctuations in the very short-term, also exercising a positive impact on real activity (0.67% within two quarters and 0.29% in the long-term) and the nominal factor (0.02%, long-term). The above results, likewise for the interpretation of the other macroeconomic and financial structural shocks, are not reported for reasons of space. A full set of results is however available upon request from the authors.

The labor supply shocks accounts for 90% of employment fluctuations in the very short-term, sizably contributing to real activity fluctuations in the short- to medium-term (up to 20%). The shock exercises a positive effect on employment (0.24% in the very short-term; 1.3% in the long-term) and real activity (0.64% in the short-term; 0.18% in the medium-term), as well as a negative effect on the unemployment rate (-0.92% in the short-term; -0.58% in the long term) and the real wage (-0.7% in the short-term; -1.3% in the long-term).

The (negative) labor demand shock accounts for 90% of unemployment rate fluctuations in the very short-term. The shock exercises a positive effect on the unemployment rate (0.28% in the very short-term; 0.35% in the long-term) and a negative effect employment (-0.10% short-term), real activity (-0.07% in the very short-term; -0.17% in the long-term), and the real wage (-0.09% in the short-term; -0.33% in the long-term).

The productivity shock is the largest contributor to real activity long-term fluctuations (20%), exercising a positive stimulus on real activity at any horizon (0.3% at the 1-year horizon and 0.7% at the 10-year horizon) and a negative short-term impact on the nominal factor (-0.01%). It also positively impacts on the real short-term rate at any horizon (0.11% in the long-term).

The US fiscal deficit shock accounts for 85% of US fiscal deficit to GDP ratio fluctuations in the very short-term. It leads to a long-term contraction in employment (-0.37%), a short-term contraction in real activity (-0.23%) and to a temporary increase in the unemployment rate (0.25%). The US trade deficit shock accounts for 80% of US trade deficit to GDP ratio fluctuations in the very short-term. It leads to a long-term contraction in real activity (-0.4%) and a long-term increase in the unemployment rate (0.3%). The above dynamics are consistent with both shocks, by being net of the global aggregate demand, labor demand and supply, and fiscal stance shocks, signaling growing long-term global imbalances.

The fiscal stance shock accounts for 58% of public expenditure to GDP ratio fluctuations in the very short-term. It leads to a permanent contraction in employment (-0.84%), real activity (-0.5%) and to a permanent increase in the unemployment rate (0.73%). By being net of the shocks accounting for the state of the global business cycle (aggregate demand, labor demand and supply shocks), it is related to *excess* public expenditure dynamics.

The core inflation shock accounts for 60% of nominal factor fluctuations in the very short-term, exercising a negative impact on employment (-0.3%, long-term) and real activity (-0.24%, short-term), also increasing the unemployment rate (0.19%, short-term) and real wages (0.4%, long-term); it also triggers a permanent increase in the real interest rate (0.05%).

8.3 The financial shocks

The excess liquidity shock accounts for 35% of excess liquidity fluctuations in the very short-term and leads to a permanent contraction in the real short-term interest rate (-0.07%), as well as in the real long-term interest rate (-0.03%, implied by the 0.04% increase in the term spread following the shock).

Being contemporaneously orthogonal to macroeconomic, liquidity and interest rates shocks, the own real stock market, housing, gold, and non energy commodity price shocks bears the interpretation of speculative asset price (portfolio) shocks; the latter account for 21%, 68%, 24% and 38% of real stock market, housing, non energy commodities index and gold price fluctuations in the very short-term, respectively.

The US$ exchange rate index shock accounts for 50% of the US$ exchange rate index fluctuations in the very short-term. Due to the ordering, it is contemporaneously orthogonal to macroeconomic and liquidity/interest rate shocks, bearing therefore the interpreatation of a purely financial shock.

The risk-free rate shock accounts for 30% of short-term real interest rate fluctuations in the very short-term. Being net of the contemporaneous effect of macroeconomic and liquidity shocks, it may be interpreted in terms of a short-term bonds risk premium shock.

The oil futures market speculative shocks, i.e. the Working's-T and futures basis shocks account for 55% (each) of Working's-T and futures basis fluctuations in the very short-term, respectively. Their interpretation in terms of oil futures market speculative shocks follows from their positive impact on both the oil futures and spot price, also affecting inventories at various horizons, in addition to being orthogonal to the set of macroeconomic and financial shocks driving flow and fundamental financial oil demand;

Being contemporaneously orthogonal to macroeconomic, liquidity and interest rates shocks, the risk factors shocks measure revisions in market expectations about future fundamentals. The risk aversion, size, value, leverage, stocks' liquidity, and momentum factor shocks account for 60%, 54%, 56%, 35%, 51% and 54% of stock market volatility, size, value, momentum, stocks' liquidity and leverage factors fluctuations, respectively, in the very short-term. The term spread shock accounts for 64% of term spread fluctuations in the very short-term.

Finally, the economic and financial fragility index shock accounts for 15% of the economic and financial fragility index fluctuations in the very short-term. By being orthogonal to all the other shocks considered in the model, it then bears the interpretation of *residual* fragility shock.