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ABSTRACT

The Changing International Transmission of Financial Shocks: Evidence from a Classical Time-Varying FAVAR*

We study the changing international transmission of US financial shocks over the period 1971-2009. Financial shocks are defined as unexpected changes of a financial conditions index (FCI), recently developed by Hatzius et al. (2010), for the US. We use a time-varying factor-augmented VAR to model the FCI jointly with a large set of macroeconomic, financial and trade variables for nine major advanced countries. The main findings are as follows. First, positive US financial shocks have a considerable positive impact on growth in the nine countries, and vice versa for negative shocks. Second, the transmission to GDP growth in European countries has increased gradually since the 1980s, consistent with financial globalization. A more marked increase is detected in the early 1980s in the US itself, consistent with changes in the conduct of monetary policy. Third, the size of US financial shocks varies strongly over time, with the `global financial crisis shock' being very large by historical standards and explaining 30 percent of the variation in GDP growth on average over all countries in 2008-2009, compared to a little less than 10 percent over the 1971-2007 period. Finally, large collapses in house prices, exports and TFP are the main drivers of the strong worldwide propagation of US financial shocks during the crisis.

JEL Classification: C3, C5, F1, F15 and F4
Keywords: financial conditions index, financial markets, global financial crisis, globalization, international business cycles, international transmission channels and time-varying FAVAR

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1 Introduction

In this paper, we study the temporal evolution in the dynamic international transmission of US financial shocks. We address the following questions.

(i) How large is the impact of US financial shocks on the major advanced countries, and have their size and transmission changed over time?

(ii) Through what channels are US financial shocks transmitted both domestically and internationally, and can we identify changes in the transmission mechanism over time?

(iii) How strongly were the major advanced economies affected by the global financial crisis (which had its origin in the US and is represented here as a shock to US financial conditions) and through which channels?

We identify US financial shocks as unexpected changes in the financial conditions index (FCI) recently published by Hatzius et al. (2010). This FCI is a broad index summarizing 45 different US financial variables. Therefore, a shock to this index needs to be interpreted as surprises to 'overall financial conditions', possibly reflecting changes in credit conditions, asset prices and/or interest rates. While several previous papers have focused on the transmission of more narrowly defined financial shocks (such as credit shocks, stock price shocks or house price shocks) we propose here, as an alternative, to focus on 'shocks to overall financial conditions' or 'FCI shocks'. This choice reflects that financial markets in the US are closely linked, which has, again, become clear during the recent financial crisis, and FCI shocks may well represent the sources of financial crises. On the other hand, we are aware that the interpretation of results regarding the propagation of a broad financial shock is more difficult than that of more narrowly defined financial shocks. We will carefully assess the properties of the FCI to facilitate interpretation.

We use the FCI in combination with a newly compiled quarterly dataset for nine major advanced countries, namely the G7 countries as well as Australia and Spain, two additional large economies. The dataset contains 202 quarterly real activity, price, monetary, financial and trade variables, over the sample period 1971Q1-2009Q2.

The FCI and the common factors underlying the large set of international variables are jointly modeled in a factor-augmented vector autoregressive model (FAVAR). Each of the 202 international variables is then decomposed into a common component, which depends on the FCI and the (remaining) common factors, and an idiosyncratic component, which is related to variable-specific shocks. Shocks to the FCI are dynamically transmitted to the other variables/factors, and have therefore both a direct and an indirect impact on all the international variables.

Financial shocks that occur in the US can affect consumption and investment in the US itself, e.g. through wealth effects, changes in funding costs and financial accelerator mechanisms. A decline in demand in the US can then lead via trade to negative economic effects abroad. In addition, financial shocks can spill over to other countries via integrated financial markets through foreign asset exposure and/or contagion effects which lead to highly synchronized asset prices across countries. Factor models take into account that international variables comove and are, thus, frequently used in the international business cycle literature (e.g. Kose et al. 2003, Stock and Watson 2005b). We also believe that our setup, which allows us to include many variables that can flexibly interact with each other, permits to appropriately capture the transmission mechanism.

Our model allows for variation in the parameters of the VAR for the FCI and the factors (including changes in the variance-covariance matrix of the shocks), and in the loadings associated with the transmission of changes in the FCI and in the factors to the international variables. This TV-FAVAR specification is suggested by Eickmeier, Lemke and Marcellino (2011) and extends the constant parameter FAVAR specification introduced by Bernanke, Boivin and Eliasz (2005). Allowing parameters to change over time when studying the international propagation of shocks is important since globalization, i.e. the increased integration via trade and financial markets, may have altered the shock transmission process, and this can be accounted for by our model. Also, accounting for parameter changes due to the development of the financial sector and its relation with the real sector is crucial for the analysis of the changing transmission of financial shocks. Our model can also capture potential asymmetries in transmission as, for instance, different effects of negative and positive shocks, as well as time variation in the size of financial (and other) shocks.

Unlike the (small) existing literature on TV-FAVARs, which employs Bayesian approaches, we estimate our model by classical (i.e. Maximum Likelihood) methods. The likelihood-based approach (using the Kalman filter) is feasible and straight-forward in our context, as we use a model representation that allows equation-by-equation estimation, where each equation with time-varying parameters is represented as a linear state space model. It is important to note that the model could be likewise estimated by Bayesian methods. Conversely, many of the other time-varying FAVAR models in the literature may be estimated by classical approaches, but these would require simulation-based techniques (just like their Bayesian counterparts) or linearizations. Hence, using a frequentist rather than a Bayesian approach here is not a necessity implied by the model structure *per se* but rather a convenient choice.

With respect to the existing international transmission literature, we make four main contributions. First, we focus on the international transmission of financial shocks whereas previous studies mostly looked at the international propagation of real or monetary policy shocks.[1] There is relatively little (recent) empirical evidence on the international trans-

[1] E.g. Artis, Osborn and Perez (2006), Artis, Galvao and Marcellino (2007), Canova and Marrinan (1998), Canova (2005), Canova and Ciccarelli (2009), Eickmeier (2007, 2010), Dées and Saint-Guilhem (2009), Dées and Vansteenkiste (2007), Dées et al. (2007), Karagedikli and Thorsrud (2010), Kim (2001), Liu and Mumtaz (2009), Maier and Vasishtha (2011), Mumtaz and Surico (2009), Neri and Nobili (2010).

mission of financial shocks, including papers by Bagliano and Morana (2010), Helbling et al. (2011) and Galesi and Sgherri (2009). All these studies also use large models. They focus, however, on specific types of financial shocks (e.g. shocks to house or stock prices or credit shocks) while we focus on shocks to overall financial conditions. Also, all models employed in these three studies are based on constant parameters.

This leads to our second contribution. As noted, we use a fully time-varying model which allows us to assess to what extent there are changes in the size of US financial shocks and their transmission to the common international factors and, via them, to the entire set of variables. In this respect, our analysis is most closely related to Liu and Mumtaz (2009) who analyze the transmission of world real and monetary shocks to the UK based on a Bayesian TV-FAVAR.[2]

Third, we look at the transmission not only via the traditional trade channel, but also via variables capturing financial and asset markets such as house prices, stock prices, credit and government bond market interest rates.

Fourth, we analyze to what extent US financial shocks were transmitted to the nine countries over the global financial crisis years 2008-2009. Most observers were surprised by the (strong) extent to which the recent crisis hit major advanced economies and attributed it to either an unusually large shock, a particularly strong transmission of that shock or some combination of the two. Linear constant-parameter time series approaches would be unable to judge if shock volatility or transmission has been different compared to previous periods and would, if parameters have indeed changed, rather exclude the crisis episode from the sample. Thus, they would be unable to properly assess the impact of the 'global financial crisis shock'.

Our main results can be summarized as follows. First, positive US financial shocks (i.e. an unexpected improvement of overall financial conditions in the US) have a considerable positive impact on growth in the countries in our dataset, and *vice versa* for negative shocks. Second, the transmission to GDP growth in the European countries has increased gradually since the 1980s, consistent with financial globalization. A more marked increase is detected in the early 1980s for the US, consistent with changes in the conduct of monetary policy in this period. Third, the size of US financial shocks also varies strongly over time, with the 'global financial crisis shock' being very large by historical standards and explaining almost 30 percent on average over all countries of the variation in GDP growth during the crisis period (compared to a little less than 10 percent over the 1971-2007 period). Finally, we find that a strong collapse in exports, TFP and house prices in most countries contributed to the strong worldwide propagation of US financial shocks during

[2] Our paper is also closely related to Dées and Saint-Guilhem (2009) and Del Negro and Otrok (2008). The former paper assesses the changing transmission of US GDP shocks to major countries and regions based on a Global VAR estimated over 10-year rolling windows. The latter paper looks at the comovement between advanced economies' GDPs using a time-varying Bayesian factor approach.

the crisis.

The rest of the paper is structured as follows. The econometric methodology is explained in Section 2. Section 3 describes the US FCI and the large international dataset. Section 4 studies the dynamics of US financial (FCI) shocks and their evolving transmission to GDP growth in the US and in the other countries in our panel. Section 5 explains the detected pattern of time variation in the consequences of the FCI shock on growth, and pins down the main transmission channels. Section 6 conducts an extensive robustness analysis of the results. Section 7 concludes.

2 Econometric Methodology

2.1 The constant-parameter FAVAR model

The analysis departs from an N-dimensional vector X_t, which includes a large number of economic and financial variables for the nine countries under investigation, and is modeled with the aid of a time-invariant approximate dynamic factor model (Bai and Ng 2002, Stock and Watson 2002):

$$X_t = \Lambda' F_t + e_t \tag{2.1}$$

In equation (2.1), $F_t = (f_{1t}, \ldots, f_{rt})'$ and $e_t = (e_{1t}, \ldots, e_{Nt})'$ denote, respectively, a vector of common factors that have a major effect on all international variables and may thus be regarded as the main (common) drivers of the international economies, and a vector of variable-specific (or idiosyncratic) components. The number of common factors is generally well short of the number of variables contained in the dataset, i.e. $r << N$. In addition, F_t may contain dynamic factors and their lags. To that extent, equation (2.1) is non-restrictive. Common and variable-specific components are orthogonal. The common factors are also assumed to be orthogonal to each other, and the variable-specific components can be weakly correlated with one another and also serially correlated in the sense of Chamberlain and Rothschild (1983). The matrix of factor loadings is $\Lambda = (\lambda_1, \ldots, \lambda_N)$, where λ_i is an r-dimensional vector whose elements measure the effect of each factor on variable i, $i = 1, ..., N$.

It is assumed that the dynamics of the factors can be described using a VAR(p) model:

$$F_t = B_1 F_{t-1} + \ldots + B_p F_{t-p} + w_t, \quad E(w_t) = 0,\, E(w_t w_t') = W. \tag{2.2}$$

Since the elements of X_t are assumed to be zero-mean processes (and the respective data are demeaned), equations (2.1) and (2.2) do not contain intercepts.

Following Bernanke et al. (2005) we break down the r-dimensional vector of factors F_t into an M-dimensional vector of observed factors G_t and an $r - M$-dimensional vector of unobserved (or latent) factors H_t, i.e. $F_t = (G_t', H_t')'$. For most of the analysis, G_t is the US FCI published by Hatzius et al. (2010) (and $M = 1$). This FCI is an aggregate of 45 US financial/asset variables. We provide a detailed explanation of how the FCI is constructed and of the underlying series in the next section. By including the FCI, we will be able to identify US financial shocks (or shocks to US overall financial conditions). The 'residual' common factors H_t consist of the other factors which drive our nine countries, most likely other global shocks or shocks that occur in one country and spill over to the other countries.

The model we have described so far can be estimated in four steps. The first step is to determine the dimension of F_t , i.e. the number r of common (latent and observed) factors driving our large dataset. We set $r = 10$ as suggested by the PC_{p2} criterion of Bai and Ng (2002). Other criteria which are often used in practice (the IC_{p1} and IC_{p2}) suggest a relatively smaller number of factors (6 for the entire sample period). However, since the space spanned by the factors is estimated consistently when the number of factors is overestimated but not when it is underestimated (Stock and Watson 1998), we prefer to carry out the analysis with 10 factors.

In the second step, we estimate H_t by removing the observed factors from the space spanned by the r factors as follows. We extract the first r principal components from X_t and summarize them in $\hat{F}_t$. Next, we estimate a regression of the form $G_t = \gamma' \hat{F}_t + v_t$. H_t is then estimated as $\hat{H}_t = \hat{\gamma}_{\perp}' \hat{F}_t$ where the $r \times (r - M)$ matrix $\hat{\gamma}_{\perp}$ denotes an orthogonal complement such that $\hat{\gamma}_{\perp}' \hat{\gamma} = 0$. The matrix of (time-invariant) factor loadings Λ can be estimated by an OLS regression of X_t on $(G_t', \hat{H}_t')'$. We should note that this very easy and fast way of cleaning the factor space from the observed factor(s) yields latent factors which are mutually orthogonal and orthogonal to the observable factor(s). The 10 latent and observable factors explain a considerable fraction - 54 percent - of the variation in X_t over the entire sample period.

In the third step, we model the dynamics of $F_t = (G_t', \hat{H}_t')'$ with the aid of the VAR (2.2).

In a fourth step, we identify the US financial shocks by applying a Cholesky decomposition to the covariance matrix of the reduced-form VAR residuals where the FCI is ordered before the international factors. Using this identification scheme, we are as flexible as possible allowing all international factors to react immediately to US financial shocks. We will discuss the choice of our identification scheme in more detail and also assess robustness with respect to the identification scheme in Section 6.

2.2 The time-varying FAVAR model

In order to trace possible changes in the way the US FCI shock affects the variables of interest in the various countries, we modify the baseline FAVAR model in (2.1) - (2.2) by allowing for time variation in the parameters. To introduce the approach, we first note that the VAR equation (2.2) can be represented as

$$PF_t = \mathcal{K}_1 F_{t-1} + \ldots \mathcal{K}_p F_{t-p} + u_t, \quad E(u_t) = 0,\ E(u_t u_t') = S, \tag{2.3}$$

where P is lower-triangular with ones on the main diagonal, and S is a diagonal matrix. The relation to the reduced-form parameters in (2.2) is $B_i = P^{-1}\mathcal{K}_i$ and $W = P^{-1}SP^{-1\prime}$.

We relax the assumption of parameter constancy in four dimensions by allowing for time variation in: (i) the autoregressive dynamics of the factors $(\mathcal{K}_1, \ldots, \mathcal{K}_p)$, (ii) the contemporaneous relations captured by the matrix P , (iii) the variances of factor innovations, i.e. the elements of S in (2.3), and (iv) the factor loadings in (2.1). Thus, we consider the following time-varying version of the single equations of (2.1),

$$x_{i,t} = \Lambda_{i,t}' F_t + e_{i,t}, \quad i = 1, \ldots, N \tag{2.4}$$

and the VAR (2.3),

$$P_t F_t = \mathcal{K}_{1,t} F_{t-1} + \ldots + \mathcal{K}_{p,t} F_{t-p} + u_t, \quad E(u_t) = 0,\ E(u_t u_t') = S_t, \tag{2.5}$$

where again P_t is lower-triangular with ones on the main diagonal, and S_t is diagonal. Note that we do not associate any structural interpretation to the P or P_t matrices for the moment, the decomposition of the variance covariance matrix of the residuals just serves to render the errors in (2.3) or (2.5) uncorrelated.

Let the time-varying parameters $\{P_t, \mathcal{K}_{1,t}, \ldots, \mathcal{K}_{p,t}, \Lambda_{1,t}, \ldots, \Lambda_{N,t}\}$ be collected in a vector α_t. Note that the dimension of this vector is $r \cdot (r-1) \cdot 0.5 + p \cdot r^2 + N \cdot r$, which can be fairly large. As is common in time-varying parameter regression models, see e.g. Nyblom (1989), we assume the parameters to vary slowly over time, as independent random walks

$$\alpha_t = \alpha_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, Q), \tag{2.6}$$

where Q is a diagonal matrix.

In practice, the matrix Q could be non-diagonal, capturing commonality in some parameter movements. Our estimation procedure, described below, remains consistent also in this case, though not efficient. As an alternative, a specific structure could be imposed on Q (to reduce the number of free parameters), or a different model used for parameter evolution, e.g., a factor model. However, both these approaches impose precise patterns of commonality in parameter movements, which we prefer to avoid given the lack of a priori information on this issue.

It is worth mentioning that our time-varying FAVAR specification nests the standard FAVAR, since when all the elements of the Q matrix are equal to zero the former reduces to the latter.

Finally, we also allow for some persistence in the idiosyncratic components in (2.4), assuming that they follow a first-order autoregressive process:

$$e_{i,t} = \rho_i e_{i,t-1} + \xi_{i,t}, \quad E(\xi_{i,t}) = 0,\ E(\xi_{i,t}^2) = \sigma_i^2, \quad i = 1, \ldots, N \tag{2.7}$$

The elements of $\xi_t \equiv (\xi_{1,t}, \ldots, \xi_{N,t})'$ are assumed to be contemporaneously uncorrelated among themselves and over time, and uncorrelated with all the elements of u_t and ϵ_t, which are in turn assumed to be uncorrelated contemporaneously and over time.

2.3 Modeling volatility

A crucial point is how to model time variation in factor innovation volatility. We assume that the variance of each shock can be approximated by a function of three observable variables (lagged by one quarter) constructed as follows. We start with the time series of daily squared logarithmic changes in the US S&P 500 and weekly (due to data availability) squared changes of the BAA-AAA corporate bond spreads. Similar to Adrian and Rosenberg (2005) we apply an HP filter to each of the two series and obtain the HP trends at daily and weekly frequency, respectively. These trends are converted to quarterly frequency by taking averages over the days (weeks) of the respective quarters. As a third observable variable we use the dispersion of GDP growth forecasts across forecasters computed as the difference between the 75th and the 25th percentile of individual 1-quarter ahead forecasts for GDP growth (published in the Survey of Professional Forecasters and provided on the website of the Federal Reserve Bank of Philadelphia). Stock market volatility and forecast dispersion are widely used measures of uncertainty in the economy as, e.g., pointed out by Bloom (2009). We add to these measures the volatility of the corporate bond spread as an additional proxy. As an alternative, in the robustness Section 6 we use the squared latent factor estimates and the squared FCI as drivers of volatility. Yet, we believe that our choice of observable drivers permits to better select indicators capturing uncertainty and financial risks.

Hence, the volatility specification of the structural shock in the gth equation has the form

$$S_{gg,t} = c_g + b_g' Z_{t-1}, \tag{2.8}$$

where the scalar c_g and the vector $b_g \geq 0$ are equation-specific, and Z_{t-1} contains the three lagged observed volatility measures. We use lagged values to avoid possible endogeneity problems, but the robustness analysis in Section 6 reveals that results are quite similar when using contemporaneous values of the volatility measures.

Finally, the specification in (2.8) nests the homoskedastic case, which would arise from $b_g = 0$.

2.4 Estimation of the time-varying FAVAR model

2.4.1 The factors

The elements of $F_t = (G_t', \hat{H}_t')'$ are obtained by combining the principal component and the regression approaches to take care of the observable factor as in the case of the constant-parameter FAVAR model. We then treat the factors as observable and estimate the time-varying-parameter factor VAR and the loading equations. Note that, as argued by Stock and Watson (2002, 2008), the factors are still estimated consistently by principal components even if there is some smooth time variation in the loading parameters (see also Banerjee et al. (2008) for finite sample simulation evidence). The intuition underlying this result is that factor estimates at time t are weighted averages of the N x_i variables at time t only.

2.4.2 The cross-sectional relations

Regarding the cross-sectional relations, we put each of the N equations (2.4) into state space form. Since the idiosyncratic component in (2.4) follows an AR(1) process, rather than being white noise, it becomes part of the state vector besides the time-varying loading parameters. For the ith equation the state vector is $\tilde{\alpha}_t^{(i)} = (\Lambda_{it}', e_{it})'$. The transition equation is given by

$$\tilde{\alpha}_t^{(i)} = \Phi_i \tilde{\alpha}_{t-1}^{(i)} + \tilde{\epsilon}_t^{(i)}, \tag{2.9}$$

where $\Phi_i = \text{diag}(1_r, \rho_i)$, $\tilde{\epsilon}_t^{(i)} = (\epsilon_t^{(i)}, \xi_{it})'$, where $\epsilon_t^{(i)}$ are the respective elements of ϵ_t in (2.6), hence, $E(\tilde{\epsilon}_t^{(i)}) = 0$, and $E(\tilde{\epsilon}_t^{(i)} \tilde{\epsilon}_t^{(i)'}) = \text{diag}(q^{(i)}, \sigma_i^2)$. That is, $q^{(i)}$ contains the random-walk innovation variances of the time-varying parameters (i.e. the respective elements of Q in (2.6)) and σ_i^2 is the innovation variance of the idiosyncratic component process. The measurement equation is

$$x_{i,t} = Z_t \tilde{\alpha}_t^{(i)} \tag{2.10}$$

where $Z_t = (F_t', 1)$. We estimate the $r + 2$ hyperparameters $(\rho_i, q^{(i)}, \sigma_i)$ of the ith loading equation by maximum likelihood. We then back out the path of time-varying loading parameters using the Kalman smoother.

2.4.3 The VAR for the factors

Since our assumptions imply independence (conditional on the factors and volatility regressors) between the r equations of the VAR representation (2.5), we can likewise estimate the time-varying parameters contained in the P_t and $\mathcal{K}_{i,t}$ matrices equation by equation. For the g^{th} equation in state space form, the state vector containing the time-varying parameters is given by

$$\alpha_t^{g\prime} = (-P_{g,1,t}, \ldots, -P_{g,g-1,t}, \mathcal{K}_{g,1,1,t}, \ldots \mathcal{K}_{g,r,1,t}, \mathcal{K}_{g,1,2,t}, \ldots \mathcal{K}_{g,r,2,t}, \ldots, \mathcal{K}_{g,1,p,t}, \ldots \mathcal{K}_{g,r,p,t}),$$

where for $g = 1$, there are no P parameters showing up. Note that due to the different number of elements coming from the triangular P matrix, the dimensions of the state vectors are different for each of the r equations.

The state equation is the random walk for α_t^g,

$$\alpha_t^g = \alpha_{t-1}^g + \epsilon_t^g, \quad \epsilon_t^g \sim N(0, Q_g), \quad Q_g = \text{diag}(q_g). \tag{2.11}$$

The measurement equation is given by

$$f_{g,t} = f_t^{g\prime} \alpha_t^g + u_{g,t}, \quad u_{g,t} \sim N(0, S_{gg,t}), \tag{2.12}$$

where

$$f_t^{g\prime} = (f_{1,t}, \ldots, f_{g-1,t}, f_{1,t-1}, \ldots, f_{r,t-1}, f_{1,t-2}, \ldots, f_{r,t-2}, \ldots, f_{1,t-p}, \ldots, f_{r,t-p})$$

and $S_{gg,t}$ is given by (2.8).

In a first step, we estimate for each equation the 'hyper-parameters' (q_g, c_g, b_g) by maximum likelihood. In a second step, we filter out the time-varying parameters of each equation by the Kalman filter. We make sure that the local VAR dynamics at each time t does not imply explosive behavior. After that, the Kalman smoothing scheme is applied in the usual fashion.

We set the VAR lag length at $p = 1$. This choice is suggested both by the need of reducing the number of parameters, and by the consideration that allowing for parameter time variation likely reduces the need of longer lags.

2.4.4 Impulse response functions and forecast error variance decompositions

Given the estimated TV-FAVAR, the impulse response functions and forecast error variance decompositions provided in this paper are based on the (smoothed) parameter structure prevailing at the respective point in time. That is, they are computed in the standard way as with constant-parameter FAVARs but with a new parameter structure at each time t. Confidence bands for the impulse response functions are computed based on a bootstrap. See Eickmeier et al. (2011) for details.

2.5 Assessing the extent of parameter time variation

One may wonder whether time variation in the parameters is really needed or a constant-parameter specification would suffice. To gauge the degree of time variation we count the number of parameters, for which the standard deviation of the Kalman-smoothed parameter path is essentially zero.[3] It turns out that there is actual time variation (i.e. no 'straight-line' parameter paths) for: 22 out of the 100 parameters of the $\mathcal{K}$ autoregressive matrix (containing the dynamics of the VAR(1) for the 10 factors); 13 out of the 45 $(= 0.5 \cdot 10 \cdot 9)$ parameters of the P matrix of contemporaneous relationships of the VAR; and 792 out of the 2020 loadings (since there are 10 loadings, one for each factor, for each of the 202 variables).

[3] In Eickmeier, Lemke and Marcellino (2011) we argue why this should be a reasonable approach.

Finally, we have assessed whether there is indeed time variation in the volatilies of the shocks, i.e. whether the elements of b_g in equation (2.8) are significant. We find that 6 out of 30 ($= 3 \cdot 10$) parameters are indeed significant at the 5% level. More specifically, the FCI shock volatility is significantly related to the stock market and corporate bond spread volatilities, but not to forecast dispersion, while the latter measure significantly enters the equations for four of the other nine (latent) factors.[4]

Hence, as these are all sizable fractions, we do believe that it is important to take parameter time variation into account.

3 Data description

3.1 US financial conditions index

We use in our analysis the FCI for the US which has been recently constructed by Hatzius et al. (2010) and published on Mark W. Watson's webpage. This FCI summarizes a broad set of 45 quarterly financial variables including interest rates and spreads, credit aggregates, survey measures on credit conditions, asset prices and exchange rates and the oil price. The index is based on an unbalanced dataset and is available from 1970 onwards.

In their paper Hatzius et al. (2010) mainly focus on an FCI constructed as follows. They first purge each series in the large financial dataset by contemporaneous and lagged influences of GDP growth and inflation and then essentially estimate the FCI as the first principal component (PC) from the residuals.[5] We use instead as our FCI the first PC of the unpurged data (which they also publish) and remove other influences later when modeling the FCI together with international factors or, further below, as a robustness check, with both international factors and a few observable US macroeconomic variables in the VAR.

The FCI we use in our analysis is shown in Figure 1, panel (a). An increase in the FCI can be interpreted as an improvement of 'overall financial conditions', while a decline reflects a worsening. The evolution of the index matches with anecdotal evidence on major financial turmoils such as the financial headwinds period in the early 1990s (see, e.g., Greenspan 1994), the stock market crash in 1987, the burst of the dotcom bubble in 2001 and the global financial crisis in 2008-2009. It is also suggestive from the chart that other influences such as the business cycle are still reflected in the FCI: its troughs coincide with the official US recessions.

[4] The t-statistics for the parameters are based on the estimated standard errors obtained from the negative inverse of the Hessian of the likelihood function.

[5] More precisely, the FCI is estimated by least squares and iterative methods since Hatzius et al. (2010) use an unbalanced panel. When the panel is balanced, the solution to the least squares problem provides the PC of the data.

To facilitate interpretation of 'shocks to overall financial conditions' or 'FCI shocks' it is useful to report the variables with the largest positive and negative loadings with respect to the FCI (which are proportional to the weights). The loadings were computed based on an OLS regression of each series on the FCI where the residuals were modeled as AR(1) processes using the Cochrane Orcutt procedure. We sort the variables according to their loadings and present variables and loadings in Figure A.1 (blue line).[6] The FCI is most highly positively correlated with a number of credit variables and the Loan Performance National House Price Index. Largest negative loadings are associated with various risk spreads, bank stock market volatility and a tightening of lending conditions by banks. The exchange rate and the oil price do not appear to be major drivers of the FCI.[7]

A legitimate question is whether the weights of individual variables in the FCI are constant over time. The argument brought forward by Stock and Watson (2002, 2008) (and used in the previous section to justify our two-step estimation approach) can also justify the PC approach for the construction of the FCI: even if the weights of the various financial indicators in the index mildly change over time, 'financial conditions' can be consistently estimated by PC. The PC estimate of the FCI would therefore, according to this argument, be consistent with both constant and smoothly time-varying weights.

To assess to what extent the weights might have changed, and to further facilitate interpretation of the FCI, we estimate time-varying loadings, assuming as in the previous section a random walk evolution and AR(1) processes for the residuals. The estimated time-varying loadings are reported as red lines in Figure A.1. It turns out that averages over the entire sample period of the time-varying loadings (green lines) and the constant loadings (blue lines) are very similar. More importantly, the red lines in Figure A.1 reveal that the loadings of most variables are fairly stable over time. There are only a few exceptions. Loadings change relatively markedly for the Wilshire 5000 stock price, in particular around the major stock market turmoils (they peak around 1987 and are also large and positive in the late 1990s/early 2000s). A similar pattern (with the opposite sign) is observed for bank stock market volatility and the VIX. We also find some variation in the TED spread with (negative) troughs during the recessions. In addition, we observe a declining trend in the weight of (more traditional) bank credit (with the exception of a peak in the early 1990s) and an increasing trend in the weights of other forms of finance

[6] The loadings we report differ from the loadings provided in Hatzius et al. (2010) which are based on data from which growth and inflation influences were removed prior to estimating the FCI. Not all variables are publically available, and we only show loadings for the available (37) variables.

[7] The FCI increases with both an increase in oil prices and a real effective appreciation of the US dollar. Of all variables, the exchange rate exhibits the smallest loading in absolute terms. The positive oil price loading can be explained with oil prices being mainly determined by demand shocks rather than by exogenous oil supply disruptions as recent work by Kilian (2009) has illustrated. Hatzius et al. (2010) indeed find a small negative loading of the oil price for the purged FCI, and we can also expect exogenous increases in oil prices to worsen overall financial conditions once other influences are accounted for.

such as ABS issuances (mortgage) since the early 1990s and commercial paper outstanding over the entire period.

Interestingly, we find relatively large absolute loadings for stock prices, house prices, ABS issuance (mortgages), bank stock market volatility and the TED spread over the recent crisis period, suggesting that the most recent worsening of US financial conditions was indeed broad-based and concerned various financial market segments.

To further facilitate interpretation of the FCI, it is worth taking into account, besides the loadings, the values of the variables at each point in time. Loadings and the variables' values together inform about the contributions of individual variables or of groups of variables to the development of the FCI. Figure A.2 shows the contributions of selected groups of variables to the FCI, computed based on constant loadings (blue line) and on time-varying loadings (red line).[8] Following Hatzius et al. (2010), we distinguish between (stock and flow) quantities, interest rates and spreads, surveys, asset prices, and second moment or risk measures. The Figure reveals that quantities and interest rates and spreads have made the largest contributions to the FCI for the entire sample period. Contributions by asset prices and second moment or risk measures were particularly high around the stock market crash in 1987. Finally, again, all groups have made sizeable negative contributions to the FCI over the global financial crisis years, confirming that the crisis was broad-based. The contributions computed based on constant and time-varying loadings do not differ much.

We refer to Hatzius et al. (2010) for more details on the underlying data, the classification of the variables in the groups, and a careful analysis of the statistical properties of the FCI.

3.2 Large international dataset

The dataset comprises quarterly variables over the period 1971Q1-2009Q2 for nine major advanced countries, the US, Canada, the UK, France, Italy, Germany, Spain, Japan as well as Australia. The choice of the sample period is mainly driven by data availability. We have tried to extend the sample as far back as possible since a long period is needed to assess whether and to what extent globalization and financial deepening has changed the way US financial shocks are transmitted internationally. Another advantage is that we can compare the recent downturn with earlier periods of financial turmoil, reaching back

[8] When computing the contributions one difficulty is the fact that the dataset underlying the FCI is unbalanced. To compute the contributions based on constant loadings, we replaced missing values of the data by the product of the (constant) loadings and the FCI. The contributions were then calculated as $(\Lambda\Lambda')^{-1}\Lambda X_t^{(j)}$ where $X_t^{(j)}$ is an N-dimensional vector of which all elements are zero, except for those associated to variables belonging to group j. For the contributions based on the time-varying loadings, we set the loadings for the missing observations to the median value of the remaining loadings and proceed in the same way. The contributions are computed as described before for each t.

up to the beginning of the 1970s.

We include for each country 23 variables (if available for the entire sample period). These variables comprise several measures of real economic activity (GDP, personal consumption, total fixed investment, residential and non-residential investment, government consumption, government primary balance-to-GDP ratio, total factor productivity (TFP), industrial production, unemployment rate), aggregate price variables (GDP deflator, CPI), trade (activity and price) variables (real exports, real imports, export prices, import prices, the real effective exchange rate, the bilateral nominal exchange rate with the US Dollar) as well as monetary and financial variables (equity prices, residential property prices, private credit, short-term and long-term interest rates). Overall, the dataset contains $N = 202$ series.

Asset prices and credit were converted to real variables by division by the GDP deflator. Exchange rates are defined such that an increase reflects an appreciation of the respective currency.

Data are taken from various international institutions, including the BIS, the IMF, the OECD and the European Commission. These data are, in some cases, complemented with data from national sources. House prices are often not available and/or only at a biannual or annual basis. We take residential property prices from Goodhart and Hofmann (2008), who carefully constructed a quarterly dataset for 17 OECD countries for the period 1971-2006, and updated their data with recent data from the BIS. Other series such as TFP and the government balance-to-GDP ratios were also available only on an annual basis. We converted annual to quarterly data using a cubic spline interpolation. A nice feature of our TV-FAVAR approach is that, at least theoretically, interpolation errors and other data irregularities should only enter the idiosyncratic component of each equation, making our analysis robust since it is mostly based on the common component.

We believe that it is particularly interesting to look at the international transmission of financial shocks to financial and asset variables, in the light of the recent crisis. As noted in the introduction, there exists not yet much evidence on the international shock transmission via asset prices, credit and other monetary and financial variables.

We also believe that looking at the transmission of financial shocks to TFP is particularly interesting, especially in the crisis period. There is currently a lively debate on whether the global crisis has affected potential (or trend) growth which is strongly determined by TFP (e.g. European Commission 2009, ECB 2008, Deutsche Bundesbank 2009). Besides their most obvious impact on potential growth via credit spreads and, hence, capital costs, and capital accumulation (ECB 2008), financial crises can affect potential growth also through their effects on TFP. The European Commission (2009) argues that "[a] slow process of industrial restructuring, caused for example by credit constraints, an impaired system of capital allocation or by entrenched structural rigidities, can [...] hurt the level and growth of TFP in the medium to long term by locking resources in (relatively) unproductive activities." and "TFP growth in the medium to long run could also be curtailed by depressed investments in private Research and Development (R&D) [...]. TFP drivers, such as physical investment, R&D and innovation, may also suffer from a prolonged recession and from the shifts in attitudes towards risk which are resulting in a tightening of credit conditions and an increase in the cost of capital."

Finally, including government consumption and government balance-to-GDP ratios will help to assess to what extent the reaction of fiscal policy to the international financial crisis has been unusual.

As is common practice in factor analysis, the series are transformed in a multiplicity of ways. Stationarity, where required, is obtained by differencing; all variables are entered as differences of logarithmized values, with the exception of interest rates, unemployment rates and government balance-to-GDP ratios, which are entered in levels. The series are standardized and subsequently have a zero mean and a unit variance. Finally, we remove outliers - defined here as observations of the (stationary) series with absolute deviations from the median which exceed six times the interquartile range. Following Stock and Watson (2005a), we replace them with the median of the preceding five observations.

Table A.1 of the appendix contains a more detailed description of the series, sources and treatment of the data.

4 US financial shocks and their evolving transmission to international GDP growth

In this section we discuss the evolution of the size of US financial shocks and their transmission to the FCI and to GDP growth (as a summary measure of real activity and a key variable of interest) in the nine countries under study.

4.1 FCI shocks

Figure 1, panel (b), shows the estimated time-varying standard deviation of the FCI shocks. Wide fluctuations emerge, with large values of the volatility broadly reflecting major financial turmoils in the US over the sample period under analysis, including the four postwar financial crises as dated by López-Salido and Nelson (2010), namely the 'Bank Capital Squeeze' in 1973-1975, the 'LDC (less developed countries) debt crisis' in 1982-1984, 'the Savings and Loan Crisis' in 1988-1991, and the global financial crisis at the end of the sample period.[9] In addition, we find high levels of the FCI shock volatility

[9] According to López-Salido and Nelson (2010), these three financial crises in the US fall into the pre-global financial crisis sample under investigation. The Bank Capital Squeeze was characterized by a strain on bank capital, several bank failures as well as the risk of default of the New York city government. The LDC debt crisis was characterized by elevated risk of some Latin American governments of a default on

around the late 1970s/early 1980s which might also be associated with structural changes in financial markets (regulatory changes and financial innovation)[10], the stock market crash in 1987, the Asian and Russian crisis at the end of the 1990s, and the build-up and subsequent burst of the 'dot-com' bubble around 2001.[11] Our analysis in Section 3.1 has shown that the peaks in the volatility around 1987 and 2001 coincide with an increase in the weight of the stock price in the FCI around these years, supporting the view that financial turbulences in these years (not classified by López-Salido and Nelson 2010 as full-blown financial crises) were largely concentrated on stock markets. Finally, during the latest crisis we observe an unprecedented increase in the variance of the shock.

Next, we compute the impulse response of the FCI to its own shock, obtained as the Cholesky residual associated with the FCI equation in the TV-FAVAR. We have normalized the shock to raise the US FCI by one unit. This normalization allows us to compare further below the transmission of shocks of the same size to other variables over time.

To get a sense of the magnitude of a one-unit shock to the FCI we need to multiply the loadings of the financial variables underlying the FCI with respect to the FCI (provided as the blue line in Figure A.1) by their standard deviations (computed from the original data that are provided on Mark W. Watson's homepage). For example, a (positive) one-unit shock to the FCI is one that leads to impact increases of the Wilshire 5000 stock price index, the Loan Performance National House Price, bank credit, the oil price, the exchange rate and the 10-year government bond yield by, respectively, 1.7 percent, 1.3 percent, 0.5 percent, 7.2 percent, 0.02 percent, and 0.3 percentage points. It is also one that triggers impact declines of the spread between the 10-year government bond over the 3-month Treasury bill, the monetary aggregate MZM, and the TED spread by 0.5 percentage points, 0.6 percent and 0.2 percentage points, respectively.

Panel (c) of Figure 1 presents the point estimates of the impulse responses for all horizons and all points in time. The chart reveals that the effect of the shock to the FCI itself peaks on impact and turns to zero after two to three years. The shock seems to have a somewhat more persistent impact on the FCI over the more recent periods.

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borrowings from US commercial banks. It culminated in the US government's rescue of the Continental Illinois Bank. The Savings and Loan Crisis was reflected in bank and savings and loan failures.

[10]Structural changes in financial markets are, e.g., the phasing out of regulation Q, the spreading of securitization, the creation of an interstate banking system, the introduction of risk-oriented capital adequacy requirements and the promotion of fair-value accounting and increased competition in the interbank market. See, e.g., Boivin et al. (2010). These changes might be reflected in financial shocks but might also have led to a changing transmission.

[11]As discussed above, estimated weights of oil prices in the FCI were not particularly large around the first two oil shocks in the 1970s and 1980s. Therefore, increased volatility during these episodes was probably due more to a worsening of the financial (and banks') conditions than to oil supply disruptions.

4.2 The changing transmission of US financial shocks to international GDP growth

Panels (a) and (b) of Figure 2 show impulse response functions of GDP growth of the nine countries to the US financial shock. Over the whole sample period the FCI shock is positively transmitted on impact to all countries. There is, however, considerable heterogeneity in the magnitude of the impact effect, also before the global financial crisis; the range of the point estimates across countries is roughly between 0.2 and 0.5 percentage points. The effects at intermediate and longer horizons are relatively high for the euro-area countries and Japan and lower (or even negative) for the other countries, including the US. From the charts, it is finally also apparent that Australian growth is less affected than growth in the other countries by the FCI shocks. The next section will shed light on these relative magnitudes.

In terms of variation over time, we find that the peak effect (which occurs at very short horizons) rises discernibly over time only in Spain, and in Germany (if we consider the post 1990 period there). There is instead somewhat more time variation in the reactions at longer horizons which is, however, only marginally significant in most countries. In particular, in the euro-area countries the medium-term transmission of the FCI shock has increased since the 1980s (meaning also that the shock impact has become more persistent). The timing and the finding that changes occurred relatively smoothly would be consistent with a gradual structural change in the economies such as that implied by globalization.

In the US, we observe a more marked increase in the responses in the early 1980s, which could rather be related to structural changes in financial markets or changes in the conduct of monetary policy. Our conjecture is that better monetary policy led to a better anchoring of inflation expectations and, hence, a smaller increase in long-term interest rates and larger effects on output; see, e.g., Boivin et al. (2010) and Eickmeier et al. (2011) for evidence of a decline in the effects of (monetary policy) shocks on inflation expectations in the US.

Over the global crisis period, the impact reaction of GDP growth was in the 0.2 to almost 0.6 percentage points range. The impact effect reaches its maximum in this episode only for Spain and Germany, whereas, interestingly, the impact during the crisis is not extraordinarily high by historical standards in the other countries.[12] However, looking at the responses after eight quarters, they have peaked during the crisis in virtually all countries.

[12] This finding does not contradict the observation that the overall economic downturn during the crisis was very strong in most countries. One needs to be always aware that we are looking at normalized (same-sized) FCI shocks in this exercise. Hence, even if the impact of a same-sized shock may not have a particularly large impact by historical standards, one has to recall that the standard deviation ('average size') of FCI shocks is changing over time and that it is estimated to be exceptionally large during the recent crisis, as discussed above.

Another interesting issue to consider is the contribution of the financial shock in explaining the forecast error variance of GDP growth in the different countries over time. The relevant information for horizons one and five years is provided in Figure 2(c). The variance shares explained by FCI shocks vary notably over time, from negligible to more than 50 percent. Contributions were large in the early-1980s, with shares of around 15-50 percent, around the stock market peak in 1987 (10-30 percent), and the burst of the dot-com bubble (10-20 percent) for all countries except for Australia where the variance share explained by the FCI shock never exceeded 10 percent in the pre-crisis period.

On average over all the countries and over the 1971-2007 (pre-global financial crisis) period, the fraction of growth variability explained by FCI shocks is slightly below 10 percent at the five-year horizon. The contribution of the shock rises strongly during the 2008-2009 crisis, to almost 30 percent on average over all countries (with a range of 10-50 percent). Interestingly, the contribution in the US was not larger than in several other countries. The magnitudes are roughly consistent with Helbling et al. (2011) for a US credit shock. They also find that US credit shocks explain a slightly smaller forecast error variance share of US GDP than of a global aggregate of GDPs. The time-varying pattern of the variance decompositions thus resembles closely the FCI shock volatility pattern, graphed in Figure 1(b), suggesting that, for the variance decompositions, the variation in the size of the shocks dominates the changes in their transmission.

The exceptionally deep recent worldwide recession in 2008-2009 was therefore mainly due to a large negative US financial shock combined with a stronger propagation of that shock to Europe. The extensive robustness analysis implemented in Section 6 permits us to state that these empirical results are quite robust to alternative specification choices for the TV-FAVAR.

5 Understanding the changing transmission of US financial shocks

We now try to explain the detected pattern of time variation in the consequences of the FCI shock on growth, and to pin down its main transmission channels by looking at the effects of the FCI shock on a variety of other variables.

In theory, financial shocks that occur in the US can affect consumption and investment in the US itself, e.g. through wealth effects, changes in funding costs and financial accelerator mechanisms.[13] A decline in real activity in the US can then lead, e.g., to lower

[13] Cecchetti et al. (2010) give a useful overview on the channels through which negative financial (crisis) shocks or a worsening of financial conditions can have adverse effects. Higher interest rates, higher spreads and lower equity prices increase funding costs and reduce investment. Lower asset prices lead to negative wealth effects for households with negative consequences for household spending. Tighter financial conditions reduce financial institutions' willingness to lend. Higher risk aversion drives up risk premia and

import demand and via trade to negative economic effects abroad. In addition, financial shocks can spill over to other countries via financial integration, i.e. exposures to foreign assets which might either result in a better risk sharing and help buffering shocks or rather reinforce the international spillovers[14] and highly synchronized asset prices due, e.g., to investors' reassessment of the outlook of countries with similar fundamentals, confidence effects or herd behavior. Changes in financial conditions abroad would then, through the channels presented above, affect the real sides of the foreign economies. By how much foreign activity is affected finally also depends on the foreign policy reactions to US financial shocks. Our setup does not allow us to cleanly disentangle the different transmission channels, but we will be able to assess how financial, trade and other variables capturing the different transmission channels respond to US financial shocks.

In this section we therefore present impulse responses of selected US and other countries' variables to the US financial shocks. To save space, we do not show results for all horizons and all points in time, but focus on the effect after one year on average over specific periods. We focus first in Subsections 5.1-5.3 on 'normal' or 'tranquil' times. We consider the periods 1971-1986 and 1987-2007 with financial turmoil periods (to be defined in the next paragraph) excluded. We choose this split because 1987 is often seen as the beginning of financial globalization (see, e.g., Kose et al. 2007). In addition, other structural changes characterize the post 1986 period, namely, the growth of the financial sector and its relation with the real economy, and the 'Great Moderation' (i.e. a marked decline in the volatility of output and inflation). We will shed light on the mechanisms behind changes in the transmission of financial shocks to international GDP growth, but will ultimately not be able to cleanly separate the effects of the various structural changes that occurred after 1986.

We will then in Subsections 5.4 and 5.5 focus on impulse response functions over six financial turmoil periods, which include the financial crises as defined in Lopéz-Salido and Nelson (2010) as well as two stock market crashes during which the FCI shocks had a large explanatory power for US GDP growth (Figure 2(c)). The periods are 1972-1974 (Bank Capital Squeeze), 1982Q3-1984Q4 (LDC Debt Crisis), 1987Q4 (Black Monday), 1988Q1-

leads to a flight to quality. Lower asset prices drive down firms' and households' net worth, increasing the problems of adverse selection and moral hazard for firms and worsening the creditworthiness of households making borrowing more difficult. Changes in financial conditions may also go along with exchange rate movements. A worsening may lead to a flight to 'safe haven' currencies and reversals of capital flows which affect exchange rates and have trade effects. Finally, a worsening in financial conditions may lead to falling confidence and activity.

[14] We focus on shocks to overall financial conditions rather than on shocks affecting only a certain financial market segment. Moreover, the previous section has shown that the identified shocks simultaneously hit the US and most other major economies. We therefore anticipate that risk sharing across different segments of financial markets and different countries will be limited, and that, instead, the exposure to foreign assets will enhance international spillovers of FCI shocks.

1991Q4 (Savings and Loan Crisis), 2001Q1-2001Q4 (the burst of the dotcom bubble and the subsequent recession) and the most recent global financial crisis period from 2008Q1 to 2009Q2, the end of our sample. We choose 2008 as the beginning of the global financial crisis since it broadly marks the start of the latest recession in most countries. We will try to understand whether the transmission of US financial shocks during financial turmoils differs from that during normal times, and to what extent the latest crisis was unusual.

5.1 The changing transmission mechanism in the US

Table 1 (columns 2-3) presents impulse responses of US and the other countries' variables (in levels) to positive US financial shocks, averaged over the periods 1971-1986 and 1987-2007 with episodes of financial turmoil excluded. US FCI shocks broadly display the expected effects in the US. They raise credit as well as equity and house prices. They also increase investment and consumption, e.g. via wealth effects, changes in funding costs and financial accelerator mechanisms.

Investment increases by more than consumption. The small but positive reaction of TFP may have contributed to the positive investment reaction. A decline in the unemployment rate may have improved the income outlook and contributed to the positive consumption response. Positive demand reactions trigger price and interest rate increases. Finally, we find a countercyclical reaction of fiscal policy reflected in a decline of the government consumption-to-GDP ratio and an increase of the government primary balance-to-GDP ratio.

In terms of variation over time, we find that the effects of financial shocks on US equity prices and credit have increased between 1971-1986 and 1987-2007, and so have the effects on consumption, investment and GDP (while the effects on house prices have remained broadly stable). Smaller interest rate responses in the second period have probably contributed to these changes. This variation in the interest rate reaction seems surprising at first sight. Given that the financial sector has become more important for activity over time, one might have expected a stronger interest rate response to financial shocks. Other factors, however, seem to matter more. Part of the explanation for the decline in the effect on interest rates could be the (slightly) smaller price response over 1987-2007. A better anchoring of long-term inflation expectations and less need for monetary policy to adjust interest rates to short-lasting changes in inflation and output as a consequence of better monetary policy may be another explanation (Boivin and Giannoni 2006). Overall, these findings would support our conjecture from the previous section that changes in the transmission to GDP growth in the US could be due to changes in the conduct of monetary policy or structural changes in financial markets, which may have altered the transmission via financial markets.

5.2 Through which channels are financial shocks transmitted internationally?

5.2.1 Trade channel

To start with the trade channel, a positive reaction in US import demand can explain export increases abroad which are particularly pronounced in Germany and Italy. Imports, however, rose as well in most countries. Exports rose by much more than imports in the US as well as in Germany.

We find depreciations of the currencies in real effective terms in Japan and - to a weaker extent - in Germany, Canada and Australia and appreciations in the UK, Spain, the US and Italy over the two periods. In line with exchange rate movements, terms of trade, defined here as export relative to import prices, in both periods worsen particularly strongly in Japan and Germany while they have consistently improved in Australia. It is, however, unclear whether exchange rates and terms of trade played an important role for the international transmission of US financial shocks. The positive (negative) income effects that might have resulted from an improvement (a worsening) of the terms of trade in Australia (Germany and Japan) were not sufficient to lead to consumption responses that were systematically larger (smaller) than in the other countries. Exchange rate movements may have contributed to a particularly large increase in exports in Germany, but the link between exchange rate and export movements is less clear for the other countries. Hence, trade reactions can probably be explained with trade openness rather than with relative price movements.[15]

Related to the trade openness issue, in the previous section, Australia stood out with the smallest GDP growth responses to the FCI shocks. Table 1 (columns 2-3) shows that while Australia's consumption response is similar quantitatively to the other countries' consumption responses, Australian exports (and investment) barely move in response to the shocks. Australia is in fact less open in terms of total trade than most of the other countries in our sample, and a large share of its exports concerns hard commodities destined for China, which can likely explain the small export reaction to US financial shocks. At the same time Australian imports increase relatively strongly. All this helps explaining findings of Australia's GDP being relatively little affected.

5.2.2 Financial and monetary linkages

As concerns financial and monetary linkages, equity prices and government bond rates move mostly in line with their US counterparts and increase after positive financial shocks. Responses of house prices and credit are more scattered. They are generally positive, but

[15] This is in line with Jacob and Peersman (2011) who show, based on a two-country DSGE model, that the absorption effect (which includes the differences between the volumes of home and domestic consumption and investment) is more important than relative prices in explaining the US trade balance.

house prices decline in Germany in both periods and in Italy over the 1972-1986 period, and credit declines in Germany as well as in Spain in at least one of the two periods. The scattered house price reactions are not surprising and could be explained by differences in local supply factors such as residential construction policies, regulation and forms of finance, as well as cross-countries differences in demand factors such as the development and the aging of the population. Similar directional reactions of credit and house prices in most countries confirm the view that house price booms (busts) and an increase (a decrease) in leverage often coincide, which was particularly apparent before and during the crisis (e.g. Eickmeier and Hofmann 2010).

Positive developments of equity prices have probably contributed to positive consumption and investment responses in basically all countries. Consumption and investment were also influenced by a better labor market situation and positive TFP reactions, respectively. We also find positive price and short-term interest rate responses which, together with countercyclical fiscal policies in most countries counteracted the shocks' impact on GDP.

5.3 Changes in the international transmission mechanism after 1986

There is no clear pattern of time variation in the export and import and the fiscal policy responses between 1971-1986 and 1987-2007.

Also, the transmission to financial market variables has not increased consistently in all countries. The reactions of equity prices, house prices and credit are all discernibly larger in the second subsample compared to the first only in Spain. The impact on stock prices has also increased in Germany, the impact on house prices has also risen in the UK, and the response of credit has become larger over time also in France and, again, the UK. Greater financial linkages, thus, may explain the increased impact on growth in Europe.

In addition, we find that, over time, the pass-through of financial shocks to interest rates has declined in almost all countries, as already observed for the US. Contagion effects may have led to government bond rate movements in the eight countries under analysis similar to movements of US rates. Monetary policy in these countries may have also improved over the 1987-2007 period and is likely to have shaped interest rate reactions as well. Declines in interest rates can, together with an increase in the TFP response in most countries over time, explain why the impact on investment and consumption is generally larger in the 1987-2007 period compared to the earlier period.

5.4 Is the transmission mechanism different over financial turmoil periods?

We now turn our attention to the financial turmoils in 1973-1975 (Bank Capital Squeeze), 1982-1984 (LDC Debt Crisis), 1987 (Black Monday), 1988-1991 (Savings and Loan Crisis) and 2001 (end of the dotcom bubble) (columns 4-8 of Table 1). We will, in the following discussion of our results, focus on negative US financial shocks which were prevalent over the financial turmoil years.

For the US there is not much evidence that the transmission of financial shocks over financial turmoils differs from the transmission over normal periods. If anything, investment responses over the turmoil periods are abnormally large (except for the 1982-1984 episode). During the Bank Capital Squeeze period this is probably due to a stronger house price reaction, while during the Savings and Loan Crisis period a stronger credit response and during the 2001 turmoil larger downturns in stock prices as well as TFP (probably as a consequence of corrected productivity growth expectations and postponed investment in new technologies) are likely to be the explanation.

For other countries we detect no systematic differences between the propagation of US financial shocks in normal times and during episodes of financial turmoils in the past century.

5.5 The 2008-2009 crisis has been unusual

How has the recent global financial crisis shock been transmitted? We address this issue looking at the numbers reported in the last column of Table 1. It turns out that, although the impact of FCI shocks on US GDP over 2008-2009 is not larger compared to the 1987-2007 period (including the turmoils), we find important shifts in the contributions of the different components.

The impact (of a shock of the same size) on consumption and especially on investment in the US has increased markedly in 2008-2009, possibly due to a stronger worsening of the labor market situation (reflected in a larger increase in the unemployment rate), a much larger decline in TFP and in house prices and despite an only moderate reaction of equity prices compared to the 1987-2007 period. The result for TFP, which can possibly be explained by postponed innovation and depressed investments in R&D, is interesting in the light of recent discussions on whether the global financial crisis had an impact on trend growth which tends to be strongly influenced by TFP (e.g. European Commission 2009, ECB 2008, Deutsche Bundesbank 2009). Our results, at least, do not stand against this hypothesis.

We also find that US exports declined relatively strongly in 2008-2009 after the FCI shock. While the US Dollar depreciated in real effective terms after negative financial shocks before 2008-2009 (consistent with standard exchange rate (UIP) theories), it appreciated over the global financial crisis and possibly contributed to the negative export reaction. The movement of the US Dollar can be explained by repatriation of investments to the US in the early phase of the crisis, as well as a worldwide loss in confidence and increase in risk aversion after the bankruptcy of Lehman Brothers. This triggered substantial safe-haven flows by investors, in particular towards US government bonds, despite the fact that the crisis originated in the US (see Cecchetti et al. 2010 who describe this mechanism and also Deutsche Bundesbank 2010).

The decline in exports was, however, partly compensated by a large decline also in US imports. Finally, exceptionally strong private demand reactions were also counteracted by unprecedentedly large countercyclical fiscal policy in terms of both government consumption and primary balance-to-GDP ratios in the US.

The last column of Table 1 also provides information on the transmission of US financial shocks to the other eight countries in our sample over the 2008-2009 crisis period. As already shown in Figure 2, most countries' GDP reactions were not unusual compared to previous tranquil and crisis episodes, except for Germany and Spain. The underlying mechanism differs, however, across the two countries. Germany experienced a relatively strong decline in its exports compared to its imports. In Spain, an exceptionally strong rise in the unemployment rate, possibly caused by the burst of the housing bubble (reflected in a strong decline in house prices), worsened the households' situation and led to a marked downturn in consumption and quite a strong decline in investment. This and a collapse of exports explain Spain's GDP reaction during the global financial crisis.

In all other countries the negative effects of the crisis on GDP were dampened by a strong decline in imports and very strong countercyclical fiscal policy reactions. Import and fiscal policy reactions seem to have fully compensated exceptionally strong declines in exports and consumption in Canada and investment in the UK, Italy and Japan. In these countries the marked decline of growth was therefore mostly due to the unprecedented size of the shock.

6 Robustness analysis

In order to assess the sensitivity of the results we have presented so far to the underlying assumptions, we have carried out several robustness checks, in particular regarding the shock identification scheme and our modeling choice for the shock volatility. We now summarize the main findings, with results from two key robustness checks in the Appendix, and other results available upon request.

6.1 Shock identification

We carry out two robustness checks with respect to the identification scheme. First, we adopt an alternative identification scheme which is, again, based on a Cholesky decomposition, but where we order the FCI last. One could argue that the FCI comprises numerous fast-moving variables such as stock prices or interest rates which can react instantaneously to other disturbances while our baseline identification scheme restricts the FCI not to respond contemporaneously (although it does allow the individual financial variables which are summarized in the FCI to react immediately). The resulting estimated FCI shock volatility and the impulse response functions of growth are presented in Figure A.3. The shape of the shock volatility is broadly the same as the one from our baseline. The relative magnitudes of the peaks are, however, somewhat altered. The volatility has now its highest value in the early 1980s and its second highest value around the global financial crisis. Moreover, the short-lasting local peak around 1987 has disappeared. The transmission of the FCI shock to GDP growth is, by contrast, virtually unaffected. The correlation between the two FCI shock estimates is at 0.97.

Second, we have repeated the analysis including $M = 4$ US variables in the VAR, i.e. GDP growth, GDP deflator inflation, the Federal Funds rate and the FCI, together with factors extracted from our dataset from which we have previously excluded US variables. Thus, again, we end up with ten factors (four observables and six latent). The four US variables are modeled in the robustness analysis as block exogenous to the international latent factors, and for the identification we order the FCI after the other US observables but before the international factors. Otherwise we pursue as for our baseline. This alternative specification separates FCI shocks from other US macroeconomic shocks in a perhaps clearer manner than in our baseline model. The advantage of our baseline compared to this alternative specification is, however, that the US is modeled in the same way as the other countries, using as many variables for the US as for other countries (and being able to investigate the reactions of all these variables) and allowing for flexible interaction between US and other countries' variables. The main results of this analysis are overall very similar to our baseline (and available upon request). The local peak in the early-1980s in the volatility of the FCI shocks is less pronounced than in our baseline. The impulse responses are somewhat more persistent. Otherwise, the shapes and magnitudes of impulse responses and shock volatility are very similar. The correlation between this and the baseline FCI shock estimates is at 0.96.

In summary, these results provide evidence in favor of the robustness of our findings to the choice of the shock identification scheme. We finally note that we decided not to employ sign restrictions as opposed to contemporaneous zero restrictions due to the lack of theoretical models providing a sufficient number of meaningful and widely accepted sign restrictions.

6.2 Modeling shock volatility

In Figure A.4 we show results obtained from a specification where the shock volatility is modeled as a function of the lags of the squared FCI and latent international factors, i.e. $S_{gg,t} = \widetilde{c}_g + \widetilde{b}'_g F^2_{t-1}$. The correlation between the FCI shock estimates from the baseline and this alternative specification is quite high, at 0.97. The resulting shape of FCI shock volatility is also overall similar to the benchmark case, with the largest peak around the global financial crisis, and large values also in the early 1970s. However, there are no temporary peaks around the two stock market crashes in 1987 and 2001, and the increase in volatility in the early 1980s is subdued. The transmission of the FCI shock to growth remains qualitatively similar on impact and after one year, while at the two-year horizon there are some differences, in particular for the UK, France, Germany, Spain and Japan. Since, overall, the squared lagged factors do not seem to capture risk and uncertainty as well as the observable variables we have used in the benchmark case, we consider the benchmark results more reliable.[16]

As a second check, we have replaced the smoothed with the unsmoothed versions of the observed volatility measures to explain the changing variances of each structural shock ($S_{gg,t}$ in Section 2.3). Results are basically unaffected.

Finally, we have also repeated the analysis with contemporaneous instead of lagged values as drivers of volatility, and again the results basically do not change.

Overall, these findings provide evidence in favour of our benchmark specification, but also suggest that our main results are rather robust to changes in the modeling of volatility.

6.3 Further robustness checks

Since factors are estimated from demeaned variables (see e.g. Stock and Watson 2002), as mentioned we have subtracted its full sample average from each variable prior to FAVAR modeling. However, the means could be also time-varying. To address this potential concern, we have applied the sequential multiple breakpoint test of Bai and Perron (1998, 2003) to all series, and in case of rejection we have subtracted properly segmented rather than constant means from the series prior to estimation of our model. It turns out that the results from this alternative standardization of the variables are very similar to those presented above.

As a further robustness check we have assessed whether results based on the filtered parameter estimates differ from those based on the smoothed estimates. This addresses the concern that sudden changes in the dynamics could be watered down by the Kalman smoother, which would bias our results, especially those regarding possible asymmetries of the transmission of financial shocks. We find that impulse responses based on filtered estimates do display more high frequency movements. Our broad picture (including our results obtained from the comparison of the transmission in normal and turbulent times), however, remains the same. Hence, we prefer to stick to the smoother in our baseline exercise, since some of the additional variation from the filtered estimates could just reflect

[16] Here we are using the estimated factors as drivers of volatility. As an alternative, there could be different unobservable volatility factors. However, this case cannot be treated within our framework, since it introduces a form of nonlinearity that cannot be handled by our Kalman filter.

small sample estimation uncertainty.

Next, as discussed in Section 2.1, in our baseline specification we have estimated the unobserved factors H_t (and removed the observed factor G_t (the FCI) from the space spanned by the r factors $\hat{F}_t$) based on an orthogonal complement that was obtained from a constant parameter regression of G_t on $\hat{F}_t$. We now, alternatively, assume random walk coefficients in this regression, γ_t', and re-estimate H_t based on the orthogonal complement of $\hat{\gamma}_t'$ for each t. The resulting estimates for H_t are very similar to those based on the constant parameter specification. The trace R^2 of a regression of one type of estimated factors on the others is very high (0.91). However, the new set of estimated factors are no longer orthogonal, though they are only weakly correlated (the largest absolute correlation is 0.16). To preserve mutually uncorrelated factors and given that the latent factor estimates are very similar in both cases, we have decided to stick in our baseline to the (computationally faster) constant parameter approach.

As two final robustness checks, we have repeated the entire exercise assuming an AR(2) model for the idiosyncratic components instead of an AR(1), and we have modeled the factors with a VAR(2) instead of a VAR(1). Once more, the results are very similar.

7 Concluding remarks

In this paper we derive and explain a number of stylized facts about how US financial shocks are transmitted internationally, and how the transmission has changed over time.

The US shock is defined as an unexpected change in the Hatzius et al. (2010) Financial Condition Index. We combine the US FCI with a newly compiled dataset of more than 200 variables from nine large advanced countries: US, Canada, UK, Germany, France, Italy, Spain, Japan and Australia. The large dataset is modeled by means of a FAVAR specification, enabling us to comprehensively analyze the (virtually) entire transmission mechanism. We exploit this feature and study not only the final effects of the financial shock on GDP growth of the nine countries but also the various transmission channels, mostly through trade and financial variables.

In order to allow for and assess the extent of time variation in the transmission mechanism, we adopt the time-varying FAVAR specification introduced by Eickmeier, Lemke and Marcellino (2011), which allows for smoothly time-varying loadings, VAR coefficients and factor innovation variances and covariance. This econometric methodology therefore permits a thorough evaluation of the temporal evolution of the international transmission of the US financial shocks.

We are now in the position to answer the three main questions that we raised in the introduction.

(i) How large is the impact of US financial shocks on major advanced countries, and have the shock size and its transmission changed over time?

We find that positive US financial shocks have a considerable positive impact on the nine countries (with Australia being less affected), and *vice versa* for negative shocks. The transmission to GDP growth in European countries has increased gradually since the 1980s. We also detect a more marked increase in the early 1980s in the US. The size of US financial shocks also varies strongly over time, with the 'global financial crisis shock' being very large by historical standards.

(ii) Through what channels are US financial shocks both domestically and internationally transmitted, and can we identify changes in the transmission mechanism over time?

Improvements in US financial conditions, as reflected in an increase in asset prices and credit, trigger positive investment and (somewhat smaller) consumption reactions in the US. Positive TFP responses probably also contribute to the rise in investment. US financial shocks are propagated internationally via financial markets, trade and policy reactions. Equity and capital rates in all other countries move in line with their US counterparts and strengthen private demand also in these countries, whereas reactions of house prices and credit are more scattered across countries. Strong increases in exports which are particularly pronounced in Germany and Italy finally also contribute to the international transmission of US financial shocks. Positive effects on GDPs in all countries including the US were counteracted by increases in prices and interest rates and by countercyclical fiscal policy.

We do not find a pattern of time variation for trade and financial markets which is consistent across countries. Reactions of consumption and investment, however, have become larger in most countries due to smaller interest rate reactions and, in general, also increased reactions of TFP. We can therefore conclude that the transmission of US financial shocks to growth in the European countries has increased over time because of an increased effect in the US and, in some, but not all countries, closer international linkages via trade and financial markets. A better conduct of monetary policy which led to smaller interest rate reactions to short-lasting movements in the FCI in the US and in other countries probably contributed to the stronger transmission as well.

The transmission of US financial shocks during financial turmoils to the US and to other countries does not differ much from the transmission in normal times. If anything US investment is hit more strongly during financial turmoils.

(iii) How strongly were the major advanced countries affected by the global financial crisis and through which channels?

We find that the exceptionally deep recent worldwide recession was mostly due to a large negative US financial shock combined with a strong propagation of that shock. US financial shocks explain almost 30 percent on average (with a range of 10-50 percent) of the variation in GDP growth during the crisis period, which is very large compared to a little less than 10 percent on average over the 1971-2007 period, and also, in most countries, larger compared to other turmoil episodes.

The transmission of the global financial crisis was unusual in a number of respects. In most countries including the US the GDP response to a same-size FCI shock was not particularly large by historical standards. This masks, however, an exceptionally marked deterioration in housing markets, an abnormally strong decline in TFP and, consequently, in consumption and investment. Most countries also experienced a collapse in exports. These developments were however, in general, compensated by a strong decline also in imports as well as a very strong countercyclical fiscal policy reaction.

Spain and Germany are exceptions in the sense that their GDPs were much more strongly hit by US financial shocks over the 2008-2009 crisis than ever before. In Germany exports declined strongly relative to imports. The unusually strong downturn in Spain can, by contrast, mainly be explained with the burst of the housing bubble and a worsening of the labor market situation which led to a particularly large negative decline in consumption.

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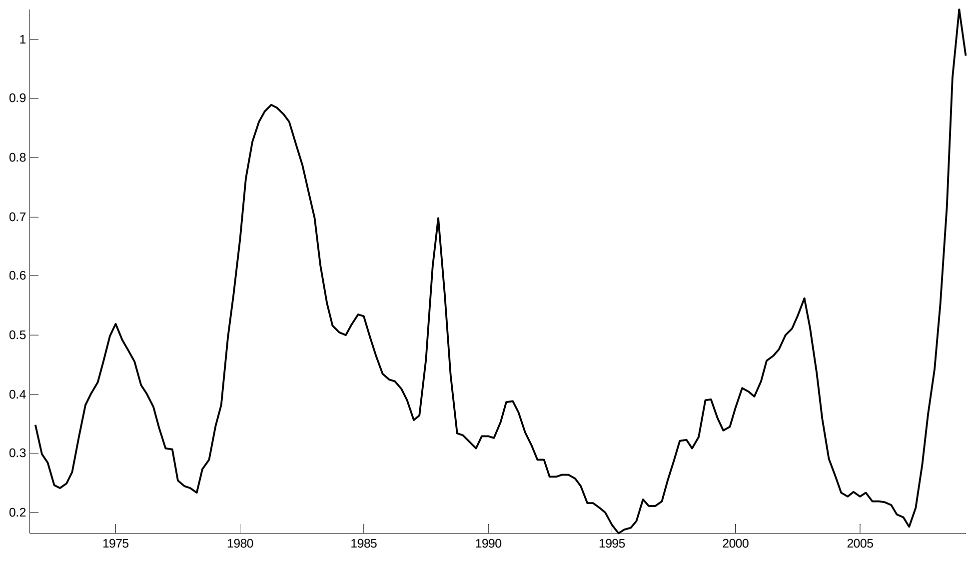
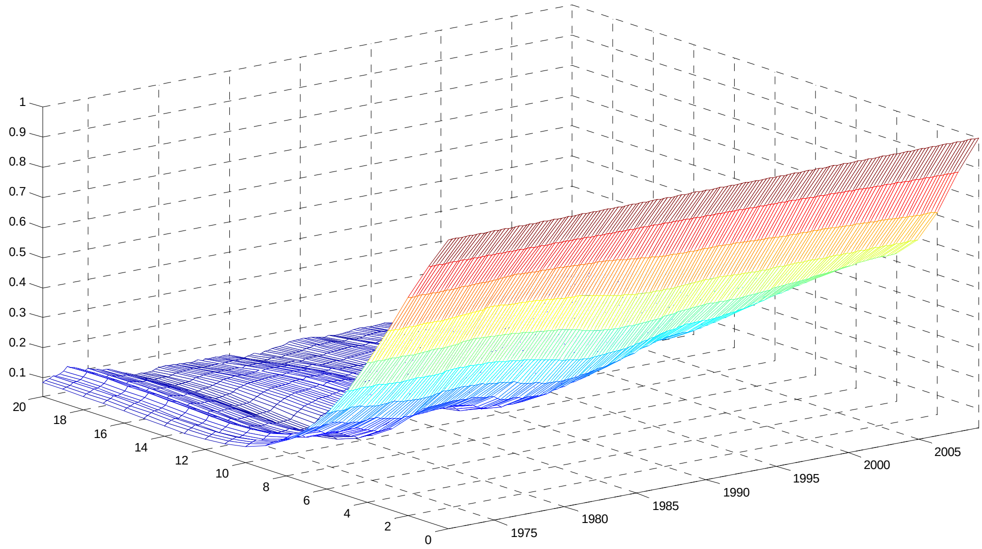
Figure 1: US financial conditions index (FCI), shock volatility, and own impulse response

(a) The FCI

(b) Time-varying FCI shock volatility



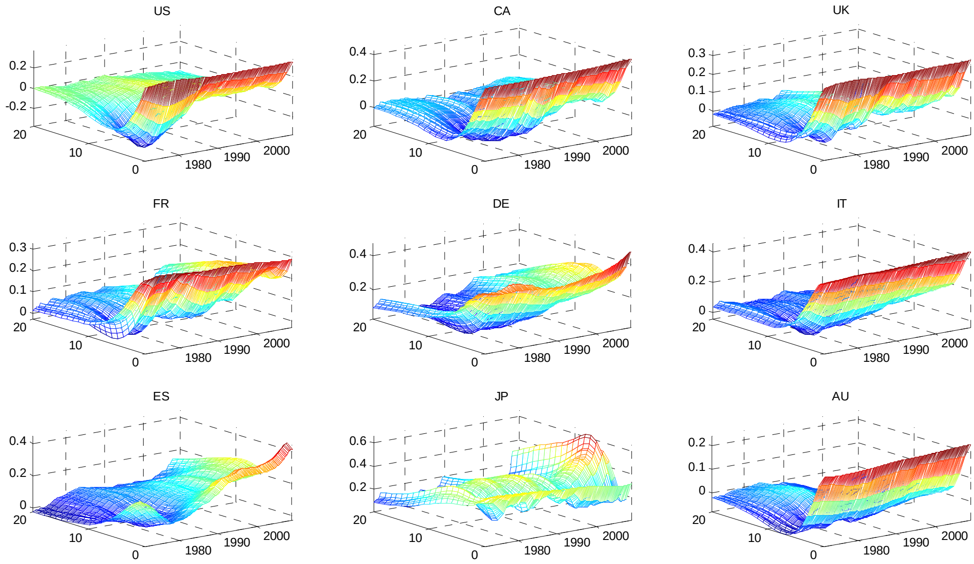
(c) Time-varying impulse responses of the FCI to FCI shocks



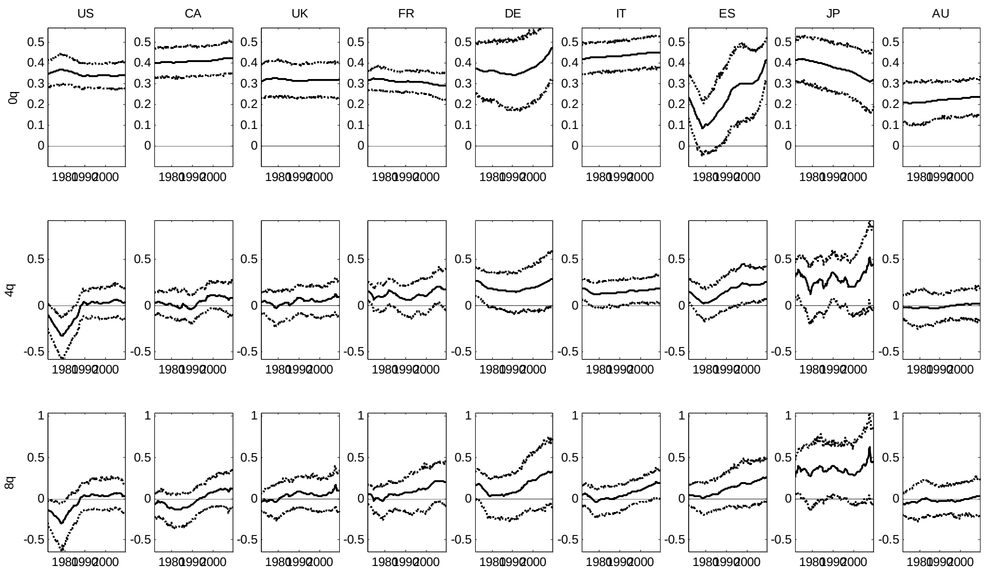
Notes: Panel (a) shows the FCI as computed by Hatzius et al. (2010) from a panel of 45 variables. The FCI data are obtained from Mark Watson’s web page. Panel (b) shows the estimated sequence of the FCI’s shock volatility. Panel (c) shows the time-varying impulse response profiles of the FCI reacting to a one-unit shock to itself.

Figure 2: Time-varying impulse response functions and forecast error variance decompositions of GDP growth

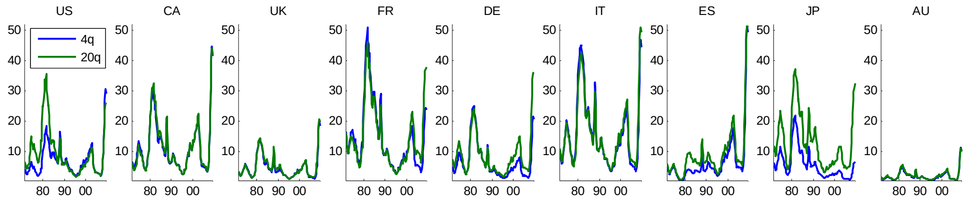
(a) Impulse responses (point estimates)



(b) Impulse responses for selected horizons (with confidence bands)



(c) Forecast error variance shares explained the FCI shock



Notes: Panel (a) shows the impulse responses of GDP growth (in percentage points) of the nine countries to a constant-size FCI shock (one unit)) over time. Panel (b) also shows these impulse responses, but only for selected response horizons (on impact, after 4 quarters, after 8 quarters) and together with 90%-confidence bands. Panel (c) displays time-varying forecast-error variance decompositions: the proportion (in percent) of unexpected changes in GDP growth over horizons of 4 and 20 quarters, respectively, which are attributable to FCI shocks.

Table 1: IRFs to expansionary FCI shocks (averages over subsamples)

	Normal times'		Financial turmoil periods					
	1972-1986	1987-2007	1973-1975	1982-1984	1987	1988-1991	2001	2008-2009
GDP								
US	0.08	0.79	0.22	0.16	0.65	0.80	0.77	0.75
CA	0.99	1.18	1.04	0.91	0.96	0.90	1.24	1.21
UK	0.71	0.86	0.83	0.75	0.79	0.91	0.82	0.91
FR	1.11	1.05	1.06	1.20	1.01	0.95	1.04	1.07
DE	1.49	1.38	1.59	1.44	1.33	1.28	1.38	1.69
IT	1.50	1.51	1.54	1.51	1.50	1.51	1.53	1.51
ES	0.51	1.39	0.78	0.45	0.79	0.98	1.41	1.75
JP	1.51	1.28	1.82	1.57	1.45	1.62	1.14	1.42
AU	0.42	0.54	0.45	0.41	0.43	0.45	0.57	0.58
Consumption								
US	0.09	0.49	0.26	0.14	0.28	0.46	0.45	0.65
CA	0.26	0.71	0.22	0.06	0.35	0.34	0.72	0.80
UK	0.23	0.33	0.32	0.24	0.30	0.43	0.27	0.36
FR	0.48	0.76	0.58	0.55	0.67	0.79	0.72	0.72
DE	1.03	0.82	1.14	1.02	0.95	0.94	0.78	0.81
IT	1.46	1.31	1.53	1.39	1.25	1.29	1.32	1.51
ES	0.48	1.00	0.67	0.36	0.66	0.53	0.96	2.00
JP	0.92	0.55	1.47	0.92	0.82	1.04	0.38	0.83
AU	0.59	0.78	0.64	0.55	0.65	0.65	0.81	0.77
Investment								
US	0.43	1.30	2.46	-0.10	1.84	2.93	2.12	2.06
CA	2.69	2.32	2.50	2.62	2.28	2.01	2.42	2.48
UK	1.74	3.72	2.49	1.76	2.89	3.53	3.83	4.29
FR	2.09	2.24	2.05	2.08	2.03	2.16	2.20	2.07
DE	1.50	0.81	1.47	1.64	1.33	1.32	0.67	0.82
IT	1.34	1.68	1.77	1.06	1.28	1.32	1.68	2.24
ES	3.27	4.46	3.43	3.17	3.74	3.92	4.49	4.99
JP	1.71	1.78	2.58	1.73	1.63	2.01	1.65	2.60
AU	0.20	0.27	0.22	0.13	-0.01	-0.05	0.40	0.40
Unemployment rate								
US	-0.17	-0.20	-0.18	-0.26	-0.17	-0.19	-0.27	-0.30
CA	-0.23	-0.16	-0.39	-0.23	-0.16	-0.19	-0.15	-0.23
UK	-0.26	-0.21	-0.30	-0.28	-0.29	-0.33	-0.17	-0.23
FR	-0.27	-0.09	-0.58	-0.04	-0.05	-0.09	-0.07	-0.09
DE	-0.33	-0.07	-0.44	-0.22	-0.15	-0.15	-0.06	0.04
IT	-0.24	-0.16	-0.42	-0.19	-0.14	-0.11	-0.19	-0.21
ES	-0.61	-0.63	-1.11	-0.36	-0.27	-0.26	-0.63	-1.15
JP	-0.10	-0.04	-0.18	-0.03	0.01	0.01	-0.07	-0.12
AU	-0.34	-0.25	-0.42	-0.41	-0.41	-0.44	-0.19	-0.16
Total factor productivity								
US	0.00	0.15	-0.03	0.01	0.05	0.07	0.17	0.23
CA	0.10	0.30	0.12	0.16	0.10	0.11	0.37	0.42
UK	0.10	0.33	0.23	-0.11	-0.07	-0.03	0.46	1.01
FR	0.34	0.42	0.58	0.11	0.25	0.31	0.49	0.50
DE	0.16	0.47	0.23	0.13	0.14	0.10	0.55	1.03
IT	0.63	0.52	0.79	0.47	0.44	0.45	0.55	0.61
ES	0.28	0.20	0.41	0.21	0.20	0.20	0.20	0.21
JP	0.38	0.64	0.13	0.37	0.45	0.45	0.73	0.96
AU								
Government consumption/GDP								
US	-0.02	-0.56	-0.25	-0.10	-0.47	-0.60	-0.53	-0.61
CA	-0.64	-0.74	-0.52	-0.56	-0.55	-0.40	-0.83	-0.75
UK	-0.79	-0.87	-0.80	-0.80	-0.80	-0.84	-0.89	-0.87
FR	-0.54	-0.52	-0.38	-0.64	-0.47	-0.36	-0.54	-0.52
DE	-1.10	-1.14	-1.22	-1.07	-1.04	-1.08	-1.12	-1.45
IT	-1.30	-1.18	-1.20	-1.29	-1.18	-1.04	-1.29	-1.09
ES	-0.32	-1.09	-0.55	-0.33	-0.61	-0.82	-1.08	-1.46
JP	-0.95	-0.56	-1.20	-0.98	-0.76	-0.85	-0.40	-0.67
AU	-0.05	-0.04	0.01	-0.06	0.04	0.09	-0.10	-0.15

Table 1 cont.

	Normal times'		Financial turmoil periods					
	1972-1986	1987-2007	1973-1975	1982-1984	1987	1988-1991	2001	2008-2009
Government primary balance/GDP								
US	0.37	0.35	0.47	0.28	0.28	0.30	0.34	0.54
CA	0.21	0.22	0.20	0.27	0.25	0.27	0.21	0.29
UK	0.13	0.27	0.28	0.06	0.16	0.22	0.29	0.43
FR	0.24	0.19	0.32	0.19	0.16	0.16	0.19	0.26
DE	0.05	-0.08	0.04	0.04	0.04	0.02	-0.06	-0.18
IT	-0.32	-0.07	-0.44	-0.24	-0.20	-0.18	0.00	-0.14
ES	0.01	0.17	0.02	0.14	-0.02	-0.03	0.16	0.76
JP	0.20	0.19	0.15	0.17	0.16	0.14	0.21	0.14
AU	0.10	0.08	0.07	0.12	0.15	0.22	0.03	0.13
GDP deflator								
US	1.34	1.24	1.43	1.33	1.28	1.30	1.21	1.25
CA	1.46	1.84	1.90	1.28	1.67	1.81	1.82	1.87
UK	2.38	1.40	2.82	2.15	1.71	1.74	1.35	1.24
FR	1.53	1.47	1.79	1.50	1.49	1.58	1.42	1.49
DE	2.81	2.95	3.39	2.64	2.78	2.90	2.92	2.91
IT	2.42	2.47	2.47	2.35	2.33	2.51	2.51	2.36
ES	2.22	2.65	2.44	2.39	2.45	2.54	2.62	2.86
JP	0.96	0.85	1.33	0.76	0.88	0.91	0.72	0.67
AU	1.75	1.99	2.09	1.67	1.66	1.90	1.97	2.11
Exports								
US	3.69	2.82	3.27	3.58	3.09	2.57	2.96	2.80
CA	1.16	1.76	1.80	1.02	0.66	0.79	2.02	3.47
UK	2.15	2.07	2.31	2.24	2.23	2.35	2.03	2.00
FR	3.03	3.03	3.11	3.04	3.16	3.12	3.10	2.70
DE	5.05	4.81	4.96	5.15	5.55	4.93	5.23	3.85
IT	4.15	4.49	4.07	4.29	4.76	4.56	4.64	4.46
ES	1.91	2.21	2.19	1.93	1.97	2.13	2.18	2.73
JP	2.67	2.25	2.71	2.81	2.73	2.81	2.06	1.38
AU	0.49	0.51	0.96	0.75	0.69	0.89	0.58	0.39
Imports								
US	0.04	1.75	-0.12	0.30	1.61	2.00	1.32	2.01
CA	-0.97	1.61	0.82	-2.66	0.03	-0.13	2.17	3.76
UK	2.77	3.26	3.33	2.88	3.13	3.61	3.15	3.30
FR	2.72	2.97	2.86	2.76	2.86	2.97	3.00	2.98
DE	2.71	2.45	2.78	2.90	2.99	2.85	1.50	2.50
IT	4.53	4.30	4.79	4.57	4.32	4.44	4.21	4.09
ES	3.66	5.12	4.26	3.18	3.80	4.21	5.14	7.19
JP	2.46	2.19	2.92	2.40	2.21	2.44	2.21	2.23
AU	3.01	2.59	2.95	2.80	2.50	2.18	2.86	2.50
Real effective exchange rate								
US	1.39	1.68	0.86	2.34	2.27	3.01	1.75	-0.19
CA	-0.59	-0.43	-0.11	-0.83	-0.91	-0.79	-0.50	0.03
UK	3.61	1.32	2.91	3.76	2.68	2.11	1.10	1.30
FR	0.54	-0.23	0.38	0.63	0.43	0.31	-0.39	-0.44
DE	-0.83	-0.75	-1.13	-0.90	-0.86	-1.03	-0.76	-0.82
IT	0.42	0.43	0.30	0.66	1.30	1.91	-0.44	-0.08
ES	3.01	1.16	3.10	3.60	3.06	3.17	0.63	0.23
JP	-5.04	-5.16	-5.74	-5.57	-5.91	-7.46	-3.78	-5.22
AU	-0.51	-1.97	0.48	-0.83	-2.11	-2.27	-2.12	-0.68
Terms of trade								
US	-2.02	2.45	-4.47	0.53	-8.66	-6.08	-1.55	0.42
CA	1.20	-0.60	2.09	0.44	3.39	3.73	0.58	0.93
UK	0.14	-0.44	0.11	0.29	-0.01	0.15	-0.81	-0.41
FR	-1.31	-1.19	-1.07	-1.41	-1.40	-1.02	-1.47	-0.91
DE	-2.88	-2.94	-2.82	-2.76	-2.82	-2.71	-3.11	-2.74
IT	-1.43	-1.24	-1.19	-1.31	-1.15	-0.91	-1.38	-1.19
ES	-3.55	-0.48	-2.84	-4.69	-2.37	-0.94	-0.54	-1.69
JP	-4.77	-4.25	-5.31	-5.54	-4.42	-5.04	-4.28	-1.51
AU	1.40	3.72	1.80	0.86	1.22	1.77	4.22	5.20

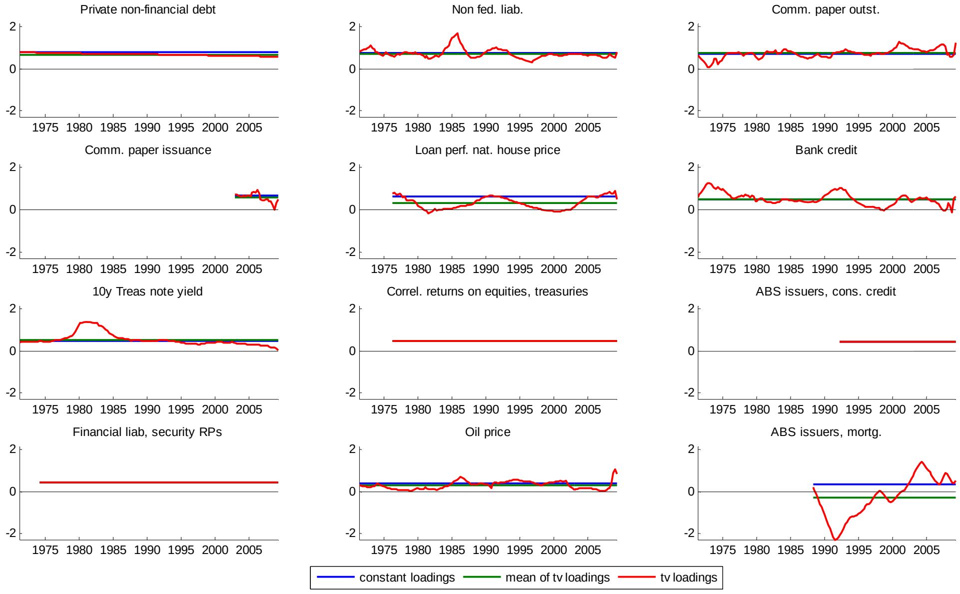
Table 1 cont.

	Normal times'		Financial turmoil periods					
	1972-1986	1987-2007	1973-1975	1982-1984	1987	1988-1991	2001	2008-2009
Short-term interest rate								
US	1.40	0.64	1.74	1.13	0.70	0.82	0.63	0.62
CA	1.07	0.67	1.17	0.89	0.91	0.93	0.64	0.74
UK	0.73	0.85	1.21	0.68	1.24	1.12	0.90	0.98
FR	0.81	0.29	1.29	0.61	0.74	0.57	0.45	0.82
DE	0.47	0.22	0.61	0.47	0.38	0.22	0.30	0.13
IT	0.54	0.22	1.42	-0.09	0.33	0.17	0.42	0.68
ES								
JP	0.58	0.09	0.57	0.28	0.38	0.31	0.08	-0.02
AU	0.75	0.86	1.13	1.02	2.10	2.12	0.74	1.23
Long-term interest rate								
US	0.62	0.52	0.67	0.56	0.55	0.54	0.52	0.47
CA	0.67	0.48	0.77	0.55	0.60	0.64	0.42	0.58
UK	0.23	0.19	0.38	0.15	0.15	0.16	0.19	0.17
FR	0.43	0.25	0.65	0.22	0.30	0.30	0.22	0.16
DE	0.37	0.24	0.47	0.28	0.25	0.25	0.23	0.17
IT	0.26	0.37	0.53	-0.06	0.17	0.18	0.43	0.40
ES	0.39	0.35	0.61	0.13	0.20	0.29	0.36	0.25
JP	0.27	0.06	0.47	0.12	-0.01	0.06	0.04	0.03
AU	0.31	0.39	0.28	0.36	0.60	0.56	0.35	0.19
Equity price								
US	9.90	12.54	6.97	20.03	12.78	11.06	13.25	2.71
CA	3.26	1.56	2.34	2.97	1.68	0.18	1.72	2.09
UK	1.01	1.40	1.65	0.94	0.82	1.28	0.91	2.15
FR	7.06	6.55	6.05	6.92	6.46	5.68	6.34	7.14
DE	3.38	13.92	1.49	4.44	25.50	23.82	16.76	1.81
IT	10.31	11.38	7.20	9.40	9.26	9.43	10.44	9.46
ES	8.80	12.22	5.87	20.95	11.55	9.67	13.41	1.11
JP	6.28	5.91	7.02	6.01	5.40	5.51	5.53	6.78
AU	2.62	2.89	1.61	1.69	-0.90	-1.08	3.71	3.59
House price								
US	1.54	1.55	2.94	0.59	0.22	0.38	1.27	4.62
CA	1.27	1.02	1.21	0.91	0.63	0.23	1.15	1.23
UK	4.16	7.53	3.48	2.15	1.90	2.06	8.87	17.39
FR	2.03	2.20	3.03	0.97	0.50	0.07	2.64	6.81
DE	-1.45	-2.20	-2.17	-1.34	-1.66	-1.95	-2.17	-2.49
IT	-0.10	0.12	-0.41	-0.36	-0.26	-0.56	0.34	0.06
ES	1.17	3.18	2.27	0.22	0.54	0.65	3.71	5.12
JP	2.12	2.47	1.32	1.68	2.05	1.75	3.06	3.80
AU	0.02	0.23	0.06	-0.46	-0.72	-0.88	0.69	-0.25
Credit								
US	1.47	1.60	1.50	1.33	1.61	1.85	1.54	1.35
CA	1.54	0.63	0.67	1.72	1.44	1.29	0.67	-1.51
UK	1.75	3.40	2.06	1.14	2.19	3.16	3.91	1.01
FR	0.97	2.19	1.03	0.81	1.41	1.61	2.29	2.11
DE	-1.52	-2.59	-2.17	-1.35	-1.70	-2.06	-2.62	-3.04
IT	0.10	0.46	0.36	0.11	0.31	0.22	0.61	0.61
ES	-1.67	2.42	-0.90	-2.94	-1.00	-0.69	5.57	0.98
JP	1.20	1.59	1.64	1.20	1.40	1.72	1.49	1.62
AU	1.35	1.65	1.28	1.27	1.35	1.33	1.71	1.74

Notes: IRFs refer to the levels of the variables and the 1-year horizon. In percentage points (interest rates, unemployment rate, government consumption/GDP), in percent (all other variables). Columns 2-3 show IRFs during ‘normal’ times (without financial turmoils), columns 4-9 show IRFs during financial turmoil periods. For details on the dating, see the text. 1973-1975 refers to 1973Q1-1975Q4 and the Bank Capital Squeeze, 1982-1984 refers to 1982Q3-1984Q3 and the LDC Debt Crisis, 1987 refers to 1987Q4 and the Black Monday stock market crash, 1988-1991 refers to 1988Q1-1991Q4 and the Savings and Loan Crisis, 2001 refers to 2001Q1-2001Q4 and the burst of the dotcom bubble, and 2008-2009 to 2008Q1-2009Q2 and the global financial crisis.

Appendix

Figure A.1: Loadings of financial variables with respect to the FCI



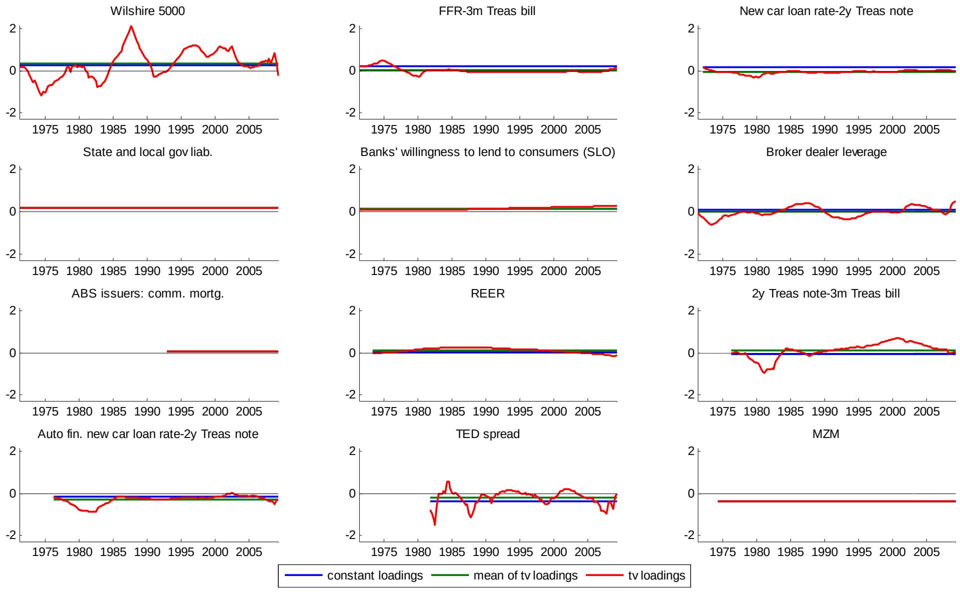
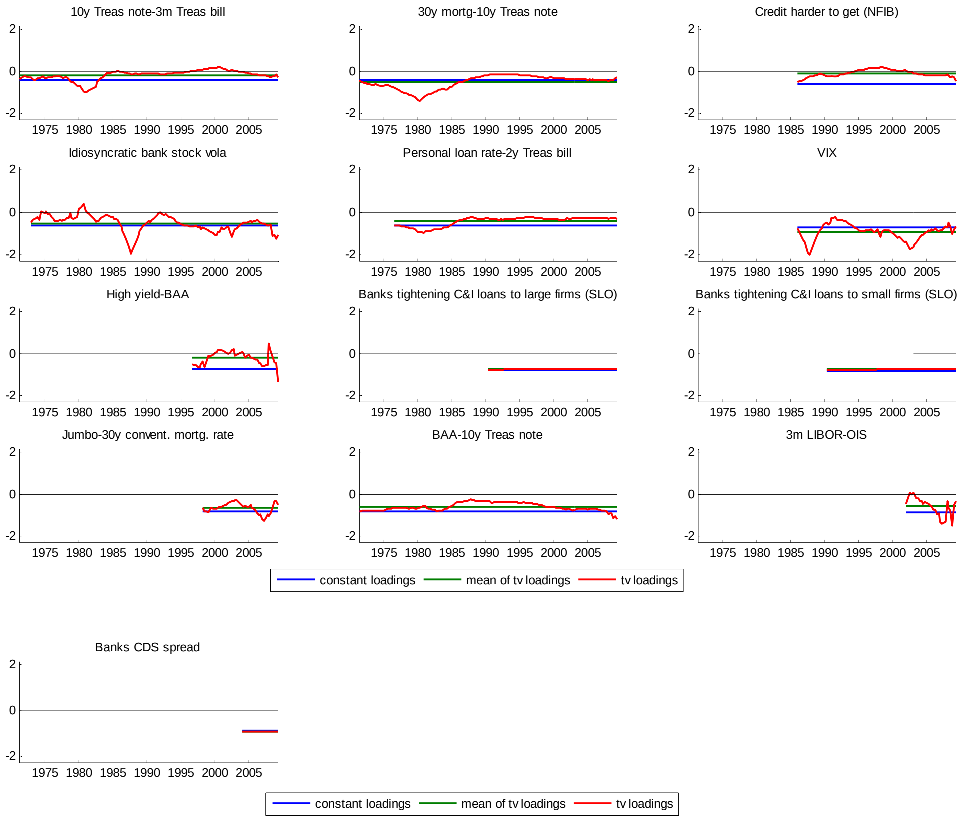


Figure A.1 cont.



Notes: The estimates of the loadings are based on a one-factor model where the factor is the first PC (our FCI) extracted from the 45 financial variables. This FCI is provided on Mark. W. Watson's webpage. AR(1) processes for the residuals are allowed for, in the constant parameter case using the Cochrane-Orcutt procedure and in the time-varying parameter case using the estimation procedure described in the methodological section of the paper. Some of the 45 variables are not available publically, and we only provide results for the available variables. For the presentation of the results, variables are ordered with respect to their (constant) loadings.

Figure A.2: Contributions of groups of financial variables in the FCI

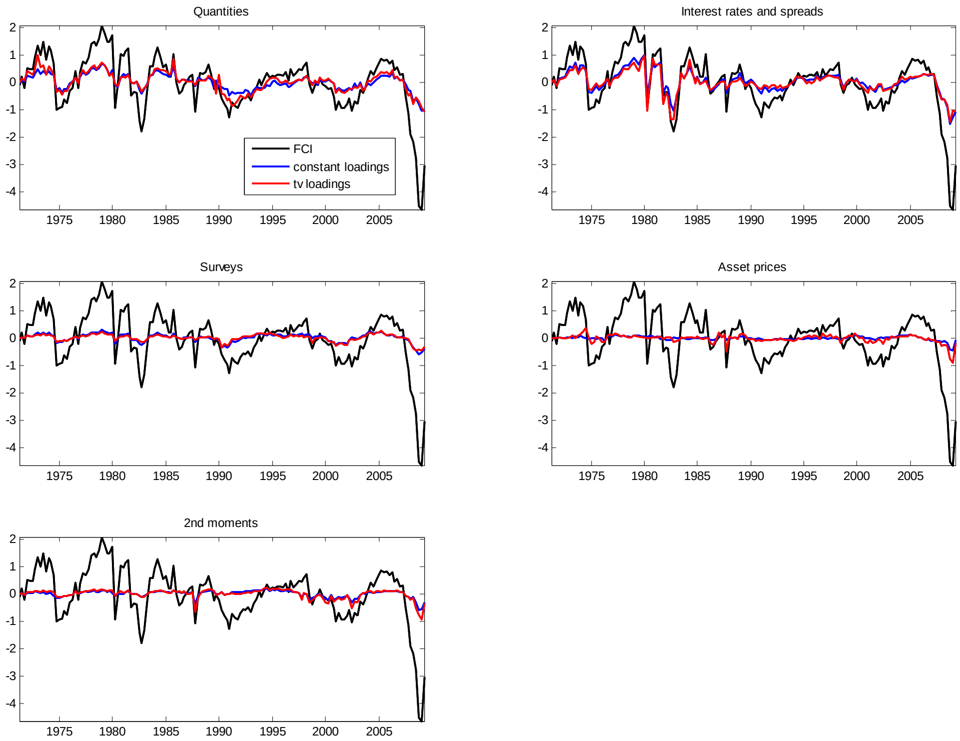
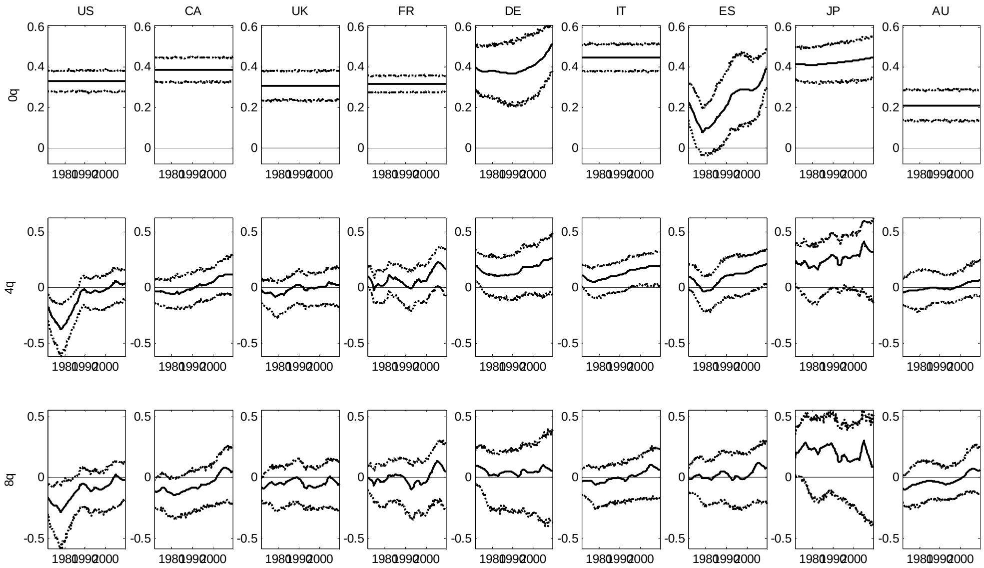


Figure A.3: Robustness analysis I: FCI ordered last

(a) Time-varying FCI shock volatility

(b) Time-varying impulse response functions for selected horizons

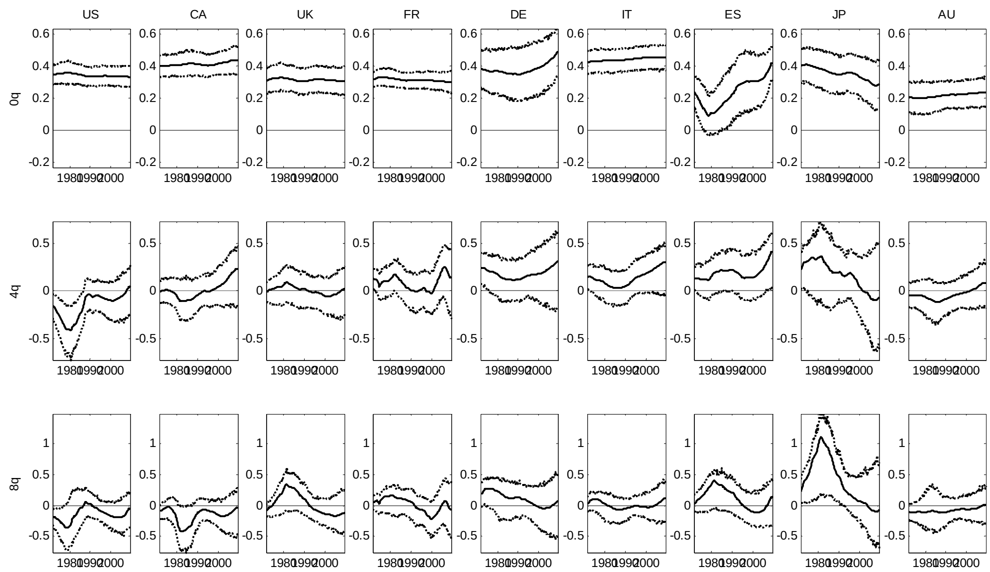


Notes: see Figure 3.

Figure A.4: Robustness analysis II: Shock volatility as a function of past squared (latent and observed) factors

(a) Time-varying FCI shock volatility

(b) Time-varying impulse response functions for selected horizons (with confidence bands)



Notes: see Figure 3.

Table A.1: Data included in the factor model

Variable	Source	Treatment
GDP	OECD, ECO	1
Private final consumption	OECD, ECO	1
Gross fixed capital formation	OECD, ECO	1
Residential gross fixed capital formation	OECD, ECO	1
Non-residential gross fixed capital formation	OECD, ECO	1
Government consumption	OECD, ECO	1
Government primary balance/GDP	OECD, ECO	0
Industrial production	OECD, ECO	1
Unemployment rate	OECD, ECO	0
Exports of goods and services	OECD, ECO	1
Imports of goods and services	OECD, ECO	1
Total factor productivity	EU Commission, AMECO	1
GDP deflator	OECD, ECO	1
Consumer price index	OECD, ECO	1
Export prices	OECD, ECO	1
Import prices	OECD, ECO	1
Equity price (real)	OECD, ECO	1
Residential property price (real)	Hofmann/Goodhart (2008) and BIS	1
Private credit (real)	BIS	1
Short-term interest rate	OECD, ECO and IMF, IFS	0
Long-term interest rate	OECD, ECO and IMF, IFS	0
Real effective interest rate	BIS	1
Bilateral exchange rate with US Dollar	Federal Reserve Board	1

Notes: 0: levels, 1: log difference; equity prices, residential property prices and domestic credit were converted into real variables by division by the GDP deflator.