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Keywords: Financial stress index, Financial Systems, Recessions, Slowdowns, Financial Crises.

JEL classification: E5, E6, F3, G2, G14.

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Financial stress and economic dynamics: An application to France

Sofiane Aboura* and Björn van Roye†

June 19, 2013

Abstract

In this paper, we develop a financial stress index (FSI) for France that can be used as a single composite indicator for the state of financial stability and financial fragilities in France. We take 17 financial variables from different market segments and extract a common stress component using a dynamic approximate factor model. We estimate the model with a combined maximum-likelihood and EM algorithm allowing for mixed frequencies and an arbitrary pattern of missing data. To gain insights of how financial stress affects economic activity, we employ a Markov-Switching Bayesian VAR (MSBVAR) model. We present the smoothed state probabilities and regime dependent impulse responses.

Keywords: Financial stress index, Financial crises, Financial Stability, Macro-financial linkages, Bayesian Markov-Switching VAR.
JEL classification: E44, F3, G01, G20, G14.

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1 Introduction

The financial crisis following the collapse of Lehman Brothers in 2008 led to severe recessions in industrialized countries. In the euro area, the crisis was exacerbated by strongly increasing government debt positions of several member states and systemic banking crises due to a high exposure of commercial banks. The potential impact of financial shocks had been dramatically underestimated before the financial crisis, as central banks had mainly focused on price stability and banking regulations had been further relaxed over the past decade.

Before the financial crisis, developments on financial markets had only a marginal role in most macroeconomic models (Borio (2011b)). Therefore, the vast majority of these models did not take into account imbalances in financial accounts and financial stress.[1] However, for policy makers, it is crucially important to enhance theoretical and empirical methods for detecting potential misalignment on financial markets at an early stage. In particular, major challenges are to (1) improve the monitoring of financial stability, (2) identify and foresee potential sources and causes of financial stress and (3) elaborate and communicate the effects of financial stress on the economy.

Against this background, monitoring and supervising the soundness of the financial system is eminent for both the monetary and fiscal authority. Particularly, a detailed analysis of financial stress is one major tool in a broader micro- and macro-prudential policy framework. To this end, the recent events have led to a re-orientation of financial stability for central banks, regulation authorities and policy makers in the meantime. Many institutions have begun intensifying its monitoring of financial variables such as stock market indicators, volatility measures and credit aggregates. In addition to monitoring single indicators independently, many institutions have begun to capture a general development of whole financial markets in composite indicators.[2] The European Central Bank (ECB), the Federal Reserve, the International Monetary Fund (IMF), the Orga-

[1] Some structural models already included financial variables, such as the financial accelerator model of Bernanke et al. (1999) and Iacoviello (2005), who modeled asset prices in an otherwise standard structural macroeconomic model.

[2] For a detailed description of the necessity of building financial stress indexes for policy makers, see Gadanecz and Jayaram (2009) and Borio (2011a).

nization for Economic Co-operation and Development (OECD) and the Bank for International Settlement (BIS) have developed financial stress indexes for different countries to assess and monitor their current states of financial stability.[3]

In addition to monitoring and supervising the financial system, a financial stress analysis is important for understanding the effects of financial shocks on the economy. From both a theoretical and empirical perspective, the effects of financial stress may be considerable. Economic theory suggests that increases in financial stress lead to changing behavior of private sector investment and consumption. While effects through the investment channel are driven by long-term interest rates and the user costs of capital, the effects through the consumption channel are mainly driven by wealth and income effects. Higher risk perception of market participants and increasing uncertainty may lead to a downturn in the business cycle. Paries et al. (2011) show that increases in money market spreads decrease bank lending, which directly reduces economic activity. In addition, Bloom (2009), Baker et al. (2012), Basu and Bundick (2012), Christiano et al. (2013), and Bonciani and van Roye (2013) show that increasing uncertainty directly leads to economic contractions.

Empirical evidence suggests that financial stress leads to economic contractions (Cardarelli et al. (2011), Davig and Hakkio (2010), Hakkio and Keeton (2009), and Cevik et al. (2012)). Holló et al. (2012) show that increases in the Composite Index of Systemic Stress (CISS), that is constructed by the ECB for its macroprudential analysis, lead to persistent declines industrial production in the euro area if the CISS exceeds a certain threshold. Similarly, van Roye (2013) shows contractionary business cycle effects for Germany. Finally, Hubrich and Tetlow (2012) investigate the impact of the financial stress index developed by the St. Louis Federal Reserve on economic activity in the U.S. using a five-variable Markov-Switching Bayesian Vector Autoregressive Model (MSBVAR). They also find evidence that economic dynamics are regime dependent, conditional on a high- or low-stress regime.

The definitions of financial stress vary across the literature. In general, financial stress is synonymous to the state of financial instability. Financial instability

[3] See Holló et al. (2012), Hakkio and Keeton (2009), Cardarelli et al. (2011), Guichard et al. (2009) and Ng (2011).

itself has quite different definitions and different dimensions. While measuring price stability is fairly straightforward, financial instability is not directly observable and it is difficult to measure. Therefore, several approaches have been introduced to capture financial instability. In this chapter, we define financial stress as a mixture of uncertainty and risk perception. In fact, Gilchrist and Zakrajsek (2012) show that periods of high uncertainty are also associated with higher risk perception, i.e. rising credit spreads. We exploit this co-movement of uncertainty and risk perception by using a dynamic factor model that identifies a common underlying component of these two measures. While uncertainty is mostly reflected in the second moments of the variables, risk perception is captured in the first moments. High levels of uncertainty and high risk premia create a situation in which the financial system is strained and its intermediation function is impaired. We closely follow the econometric methodology of van Roye (2013), who constructs a financial stress index for Germany.

This chapter proceeds as follows. Section 2 explains the modeling methodology and the estimation technique. Section 3 presents the indicator and evaluates its ability to capture the main systemic events that have occurred in France. Subsequently, in section 4, we analyze the effects of financial stress on economic dynamics using a Markov-Switching VAR model. Section 5 summarizes the main results and concludes.

2 Methodology

The literature proposes many different approaches to aggregate data into a single indicators. Researchers typically face two trade-offs when being confronted with data collection and aggregation methods. These trade-offs also apply to to construction of financial stress indexes.[4] The first trade-off is the data selection with respect to the time span. In general, a large sample with a long history is desirable to test the indicator's predictive properties and statistical characteristics over the business cycle. However, many financial variables that are particularly reflective for financial stress, e.g. credit default swap premia and money market spreads, are only available over very recent time periods. In this case, a shorter data sample might be preferable because these variables might better reflect financial stress than other measures that are available for a longer time horizon. The second trade-off is the frequency at which the financial variables enter the financial stress index. This trade-off depends on the type of data used, which can be available in daily, weekly, monthly or quarterly frequencies. For instance, stock market indexes and credit default swap premia are available on a daily basis, whereas some survey indicators, such as bank lending credit standards, are only reported once in a quarter. The advantage of having higher frequency data is that the potential stress signals on financial markets can be identified at an early stage. The disadvantage is that it is significantly more volatile and usually delivers more false signals.

We address these trade-offs by using a methodology that addresses both the data frequency trade-off and the time span trade-off. First, using a dynamic factor model in combination with the Expectation Maximization algorithm allows to include time series that are available over a long time period as well as those that have a short data history. The approach also allows for treating mixed frequency data. We can include native daily, monthly and quarterly frequencies into the estimation of the financial stress index, which will ultimately be calculated on a monthly basis. In the following subsection, we will present the underlying econometric methodology of the model and provide details on the construction and transformation of the data.

[4] For a detailed description of these trade-offs and how this issue is addressed in the literature, see Kliesen and Smith (2010).

2.1 Dynamic Approximate Factor Model

In this chapter, we follow the methodology of Banbura and Modugno (2012) and van Roye (2013), estimating a dynamic approximate factor model (DFM) that allows for an arbitrary pattern of missing data and a mixed frequency estimation including daily, monthly and quarterly data in the indicator. The factor model allows us to capture the co-movement of all considered financial variables and extract the underlying latent factor that can be interpreted as financial stress. In particular, the model takes the following form:

$$y_t = \Lambda f_t + \varepsilon_t, \qquad \text{where} \;\; \varepsilon_t \;\; \sim \; iid\, \mathcal{N}(0, C), \tag{1}$$

where y_t is a matrix of financial variables, f_t is the $1 \times T$ common latent factor containing the time-varying co-movement in the $N \times T$ matrix (the common volatility factor), and Λ is a $N \times 1$ vector of the time series' factor loadings. The values in the factor loading vector represent the extent to which each financial variable time series is affected by the common factor. The $N \times 1$ vector ε_t represents the idiosyncratic component, which is allowed to be slightly correlated at all leads and lags. The dynamics of the latent factor f_t are described in the transition equation:

$$f_t = A f_{t-1} + \xi_t, \qquad \text{where} \;\; \xi_t \;\; \sim \; iid\, \mathcal{N}(0, D), \tag{2}$$

Before estimation, the time series are de-meaned and standardized. Regarding the estimation technique of the model, we closely follow Banbura and Modugno (2012) and apply a maximum-likelihood approach combined with the Expectation Maximization algorithm originally proposed by Dempster et al. (1977). This model allows for an efficient treatment of ragged edges, mixed data frequencies and an arbitrary pattern of missing data.[5]

2.2 Data

The financial variables that we include for calculating the financial stress index are in a way subjectively chosen. We select the financial variables that we believe are mostly relevant to describe the stability of the financial system. All of the data

[5] For a detailed description of the estimation technique, see Banbura and Modugno (2012), and for an application to a financial stress index, see van Roye (2013).

rely on economic fundamentals such as interest spreads, credit spreads, liquidity premia, stock market indicators and volatility measures of financial markets. First, we collect data that are directly linked to the banking sector. Beside profit expectations, risk spreads, and credit default swaps, we compute a banking sector volatility index given by a ARMA(1,1)-TGARCH(1,1) model. In addition, using a CAPM model we calculate the implicit cost of equity for commercial banks. Second, we collect general capital market data, such as bond yields, the stock returns of important French corporations, and derivatives such as CDS spreads. Third, we collect data from the foreign exchange market and calculate a nominal exchange rate volatility index. A detailed description about data sources and data transformation is provided in the following subsection.

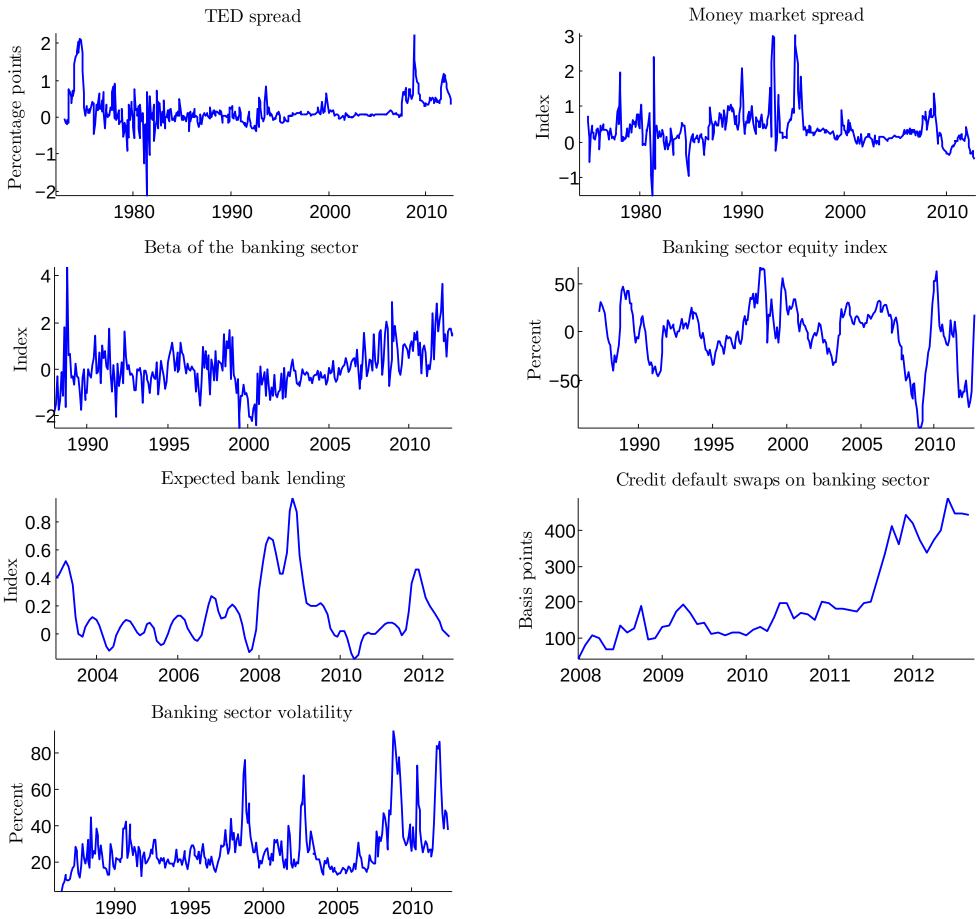
2.2.1 Variables related to the banking sector (figure 1)

The first group we consider are financial variables related to the banking sector. In particular, we calculate indicators that in some way reflect the state of financial stability in the sector of monetary financial institutions. For the banking sector, we use 7 financial variables.

TED spread The TED spread is calculated as the difference between the 3-month PIBOR/Euribor as reported by the OECD and French government treasury bills with a maturity of 13 weeks as reported by the Banque de France. The TED spread is an important indicator for interbank lending conditions. While increasing liquidity in the money market leads to a reduction, decreasing money market liquidity leads to an increase in this spread. An increasing TED spread therefore contributes positively to financial stress.

Money market spread We calculate the indicator by taking the difference of the 3-month unsecured money market rate (3-month Euribor) and the secured money market rate (3-month Eurepo). An increasing spread between these two interest rates induces a rising risk perception in the money market. Similar to the TED spread, an increasing money market spread contributes positively to financial stress.

Figure 1: *Variables related to the banking sector*



β of the banking sector The β of the banking sector is derived from the standard CAPM model and represents the sensitivity of bank stocks to general market risk. It is calculated as the covariance of bank stocks and the French stock market index SBF 250 divided by the variance of the SBF 250. Increases in β can be interpreted as a proxy for rising equity costs for commercial banks. The β of the banking sector contributes positively to financial stress.

Banking sector equity index The database consists of 6.782 daily closing prices that span the period of June, 25^{th} 1986 to June, 21^{st} 2012. This period includes both calm and extreme sub-periods. The prices are computed by Datastream as a French banking sector index. The sector includes 4 banks: BNP Paribas, Crédit Agricole, Sociéte Générale, Natixis. We calculate the first differences of this index as a measure of the state of a banking profit situation.

A decreasing equity index reflects negative profit expectations, which may put pressure on the financial sector's balance sheet. Decreasing bank equity leads to an increase in financial stress.

Expected bank lending The expected bank lending is directly taken from the ECB Bank Lending Survey. Selected country-specific results are available at certain national central banks. In our case, the Banque de France provides data for France for expected bank lending in the next 3 months. The data are only available on a quarterly basis. Increases in this indicator reflect a tightening in credit standards for private sector credit, as reported by important financial institutions in France. Increases in this indicator contribute positively to financial stress.

Credit default swaps on financial corporations The credit default swap (CDS) index is the weighted average of the 10 year maturity CDS of important French financial institutions. In particular, we include the following banks: BNP Paribas, Crédit Agricole, Dexia, Crédit Local and Société Générale. Weights are computed according to market capitalization. Because these credit default swaps indicate the default risk of financial institutions, increasing values contribute positively to financial stress.

Banking sector volatility The volatility of the French banking sector is computed from the banking sector equity index with the following methodology. First, we examine all the possible specifications within five lags to choose the appropriate volatility model. We test 25 specifications of ARMA(p,q) models with $p = 1, ..., 5$ and $q = 1, ..., 5$ in addition to 25 specifications with ARMA(p,q) + GARCH(1,1). Second, we select the more parsimonious model. Four criteria are used for comparison: the log-likelihood value, the Akaike criterion, the autocorrelogram of residuals and squared residuals and the ARCH effect test. We take into consideration the trade-off between parsimony and maximizing criteria and find that the ARMA(1,1) + GARCH(1,1) model produces the best fit. Third, we test an alternative model that allows for leverage effects by considering the contribution of the negative residuals in the ARCH effect. The ARMA(1,1) + TGARCH(1,1) model offers improvements for the considered criteria. We define the banking sector log returns as $\{B_t\}_{t=1,\ldots,T}$ with T = 6.782 daily observations. The ARMA(1,1) +TGARCH (1,1) specification is then provided as follows:

$$\log B_t = \mu_1 + \phi_1 \log B_{t-1} + \theta_1 \epsilon_{B,t-1} + \epsilon_{B,t} \tag{3}$$

with the innovations $\epsilon_{B,t}$ being functions of $Z_{B,t}$ and $\sigma_{B,t}$

$$\epsilon_{B,t} = Z_{B,t}\sigma_{B,t} \tag{4}$$

where the standardized returns $Z_{B,t}$ are independent and identically distributed, such as:

$$Z_t \hookrightarrow F_{B,Z}(0,1) \tag{5}$$

where $F_{B,Z}$ is an unknown distribution of Z. The time-varying volatility model $\sigma_{B,t}$ is given by:

$$\sigma^2_{B,t} = \omega + \alpha\left(Z_{B,t-1}\sigma_{B,t-1}\right)^2 + \gamma\left(Z_{B,t-1}\sigma_{B,t-1}\right)^2 I_{Z_{B,t-1}\sigma_{B,t-1}<0} + \beta\sigma^2_{B,t-1} \tag{6}$$

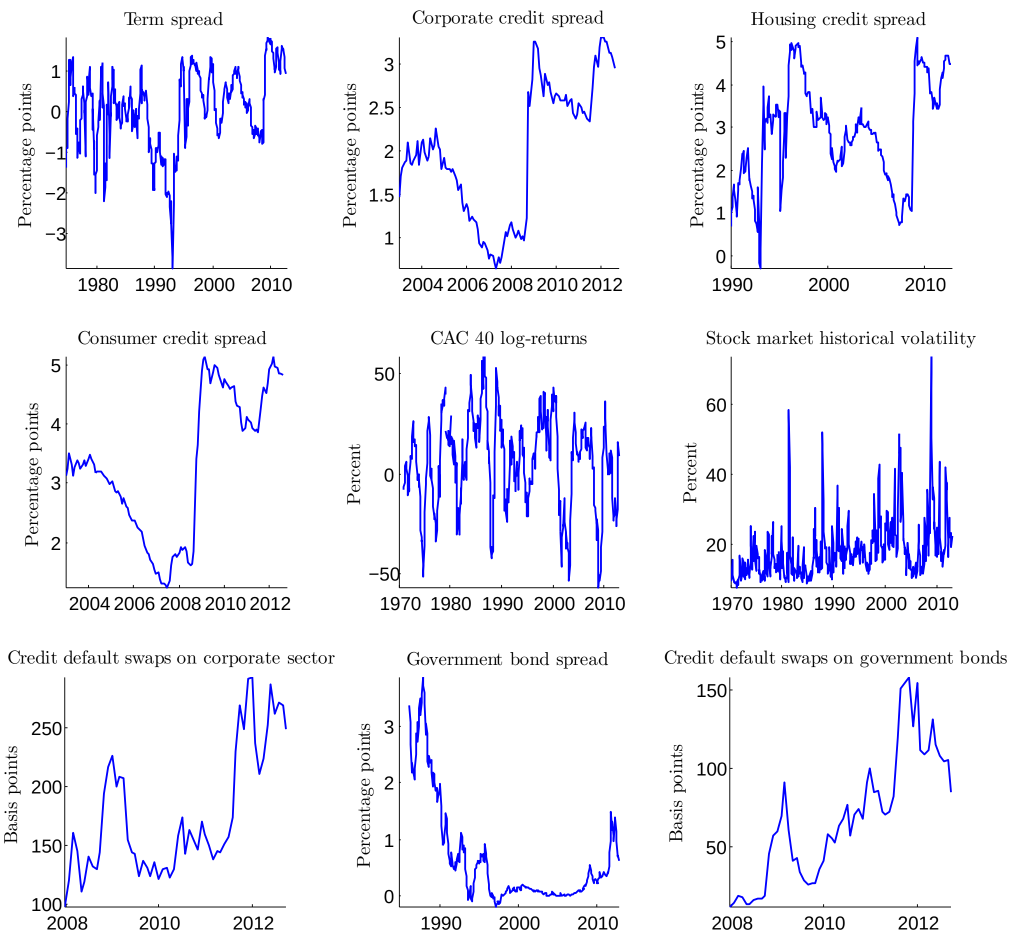
The banking sector volatility index is a proxy for uncertainty in the financial sector. Since higher uncertainty on the banking sector's outlook may concur in more restrictive lending to the non-financial sector, this index contributes to positively to the financial stress index.

2.2.2 Variables related to the capital market (figure 2)

The second group of financial variables we consider are variables related to the capital market. In particular, we consider credit spreads, bond spreads, yield indexes and credit default swaps. For the capital market variables, we choose 9 indicators.

Term spread The term spread – the difference between short-term and long-term interest rates – is an indicator for predicting changes in economic activity.

Figure 2: *Variables related to the capital market*



Usually, the term spread is positive; i.e., the yield curve slopes upward. However, many recessions are preceded by decreasing term spreads and sometimes even exhibit an inverted yield curve.[6] A decreasing term spread results in higher values of the financial stress index.

Corporate credit spread The credit spread measures the difference between the yield on one to two year loans to non-financial corporations and the rate for secured money market transactions (Eurepo) with the same maturity. An increase in this spread reflects higher capital costs for non-financial corporations which contributes positively to financial stress.

[6] For a survey on the ability to forecast output growth in industrialized countries, see Wheelock and Wohar (2009).

Housing credit spread The housing spread is calculate by taking the difference between interest rates for mortgages with an average maturity of 5 years and the yield of French government bonds with the same maturity. Rising spreads reflect increasing risk perception by banks with respect to their mortgage lending. Therefore, this indicator contributes positively to the financial stress index.

Consumer credit spread The consumer credit spread is calculated by taking the difference between the interest rates for consumer credit with an average maturity of 5 years and the yield of French government bonds with the same maturity. Rising spreads reflect increasing risk perception by banks with to consumer loans. Therefore, this indicator is contributes positively to the financial stress index.

Stock market log-returns (CAC 40) The French stock market series of log returns is a special series combining the "Indice General" stock index (January, 2^{nd} 1970 to December, 30^{th} 1987) and the CAC 40 stock index, which has been computed since December, 31^{st} 1987. The Indice General, which is the ancestor of the CAC 40, is not publicly available. For simplicity, this long series representing the French stock market is called CAC 40 log returns. This database consists of 10.671 daily closing prices. Falling stock prices contribute positively to the financial stress index.

Stock market historical volatility We construct the historical volatility series from the CAC 40 log return series. Therefore, this database consists of 10.671 daily volatilities that span from January, 2^{nd} 1970 to July, 31^{st} 2012. We follow the same methodology used for the banking sector index volatility construction. We find that the ARMA(2,4)+TGARCH(1,1) model improves the fit in all considered criteria. We define the market log-returns as $\{R_t\}_{t=1,\ldots,T}$ with T= 10.671 daily observations. The ARMA(2,4) + TGARCH (1,1) specification is as follows:

$$R_t = \mu + \sum_{i=1}^{2} \phi_i R_{t-i} + \sum_{i=1}^{4} \theta_i \epsilon_{R,t-i} + \epsilon_{R,t} \tag{7}$$

with the innovations $\epsilon_{R,t}$ being functions of $Z_{R,t}$ and $\sigma_{R,t}$:

$$\epsilon_{R,t} = Z_{R,t}\sigma_{R,t} \tag{8}$$

where the standardized returns $Z_{R,t}$ are independent and identically distributed:

$$Z_{R,t} \hookrightarrow F_{R,Z}(0,1) \tag{9}$$

where $F_{R,Z}$ is an unknown distribution of Z. The time-varying volatility model $\sigma_{R,t}$ is given by the following:

$$\sigma^2_{R,t} = \omega + \alpha \left(Z_{R,t-1}\sigma_{R,t-1}\right)^2 + \gamma \left(Z_{R,t-1}\sigma_{R,t-1}\right)^2 I_{Z_{R,t-1}\sigma_{R,t-1}<0} + \beta\sigma^2_{R,t-1} \tag{10}$$

Stock market volatility can be interpreted as aggregate uncertainty on financial markets on future economic activity (Bloom (2009)). Higher uncertainty increases potential strains on financial markets. Against this background, this index contributes positively to the financial stress index.

Credit default swaps on corporate sector The credit default swap index is the weighted average of the 10 year maturity CDS of important French corporations. In particular, we include the following firms: Accor, Alcan France, Alcatel, Allianz France, Arcelor Mittal France, Assurance Générale de France, Axa, Bouygues Télécom, Carrefour, Casino, Cie de Saint-Gobain, Danone, EDF, France Télécom, GDF Suez, Gecina, Havas and Air Liquide. Weights are computed according to market capitalization.

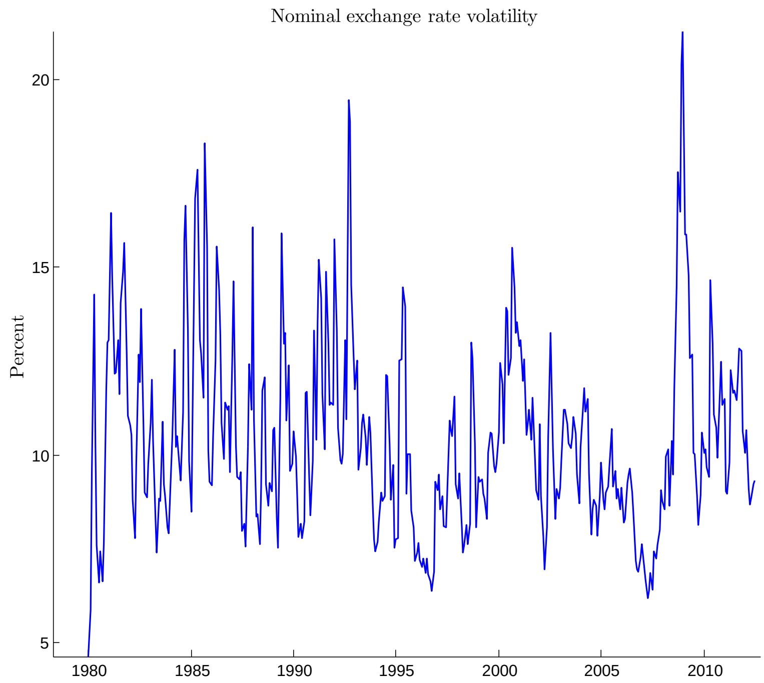
Government bond spread The government bond spread is calculated by using the average yield of French government bonds with a maturity of 10 years and subtract it from the corresponding German government bonds. An increase in this spread reflects the market's higher risk perception with respect to French government bonds and contributes positively to financial stress.

Credit default swap on 1Y Government Bonds The premium for government credit default swaps reflects a default probability of outstanding sovereign debt. If the default probability rises, tensions on banks' balance sheets and the whole financial system increase. Therefore, the government CDS affects financial stress positively.

2.2.3 Variable related to the foreign exchange market (figure 3)

The third group consists of an indicator that indicates stress on the foreign exchange market. More precisely, we calculate a nominal synthetic exchange rate volatility.

Figure 3: *Variable related to foreign exchange market*



Nominal synthetic exchange rate volatility This historical volatility series is constructed from the nominal synthetic exchange rate. This special series is the synthetic dollar-euro nominal exchange rate and is based on trade weights given by the share of external trade of each euro area member state in the total euro area trade. It is computed by the ECB. The database consists of 8.499 daily exchange rates that span from January, 7^{th} 1980 to July, $31, 2012$. We follow the same methodology used for the banking sector index volatility construction. We find that the ARMA(2,4)+TGARCH(1,1) model improves the fit in all considered criteria. We define the exchange rate log-returns as $\{E_t\}_{t=1,...,T}$ with T= 8.499 daily observations. The ARMA(2,2) + TGARCH (1,1) specification is then provided as follows:

$$E_t = \mu + \sum_{i=1}^{2} \phi_i E_{t-i} + \sum_{i=1}^{2} \theta_i \epsilon_{E,t-i} + \epsilon_{E,t} \tag{11}$$

with the innovations $\epsilon_{E,t}$ being functions of $Z_{E,t}$ and $\sigma_{E,t}$:

$$\epsilon_{E,t} = Z_{E,t}\sigma_{E,t} \tag{12}$$

where the standardized returns $Z_{E,t}$ are independent and identically distributed:

$$Z_t \hookrightarrow F_{E,Z}(0,1) \tag{13}$$

where $F_{E,Z}$ is an unknown distribution of Z. The time-varying volatility model $\sigma_{E,t}$ is given by the following:

$$\sigma^2_{E,t} = \omega + \alpha \left(Z_{E,t-1}\sigma_{E,t-1}\right)^2 + \gamma \left(Z_{E,t-1}\sigma_{E,t-1}\right)^2 I_{Z_{E,t-1}\sigma_{E,t-1}<0} + \beta\sigma^2_{E,t-1} \tag{14}$$

After the estimation, we present the factor loadings of the considered financial variables (table 1). The financial variables that contribute most strongly to the financial stress index are the historical volatility of the CAC 40, the CAC 40 log returns and the banking sector volatility. The term spread and the government bond spread do not have a significant impact on financial stress in France.

Table 1: *Factor loadings of the DFM*

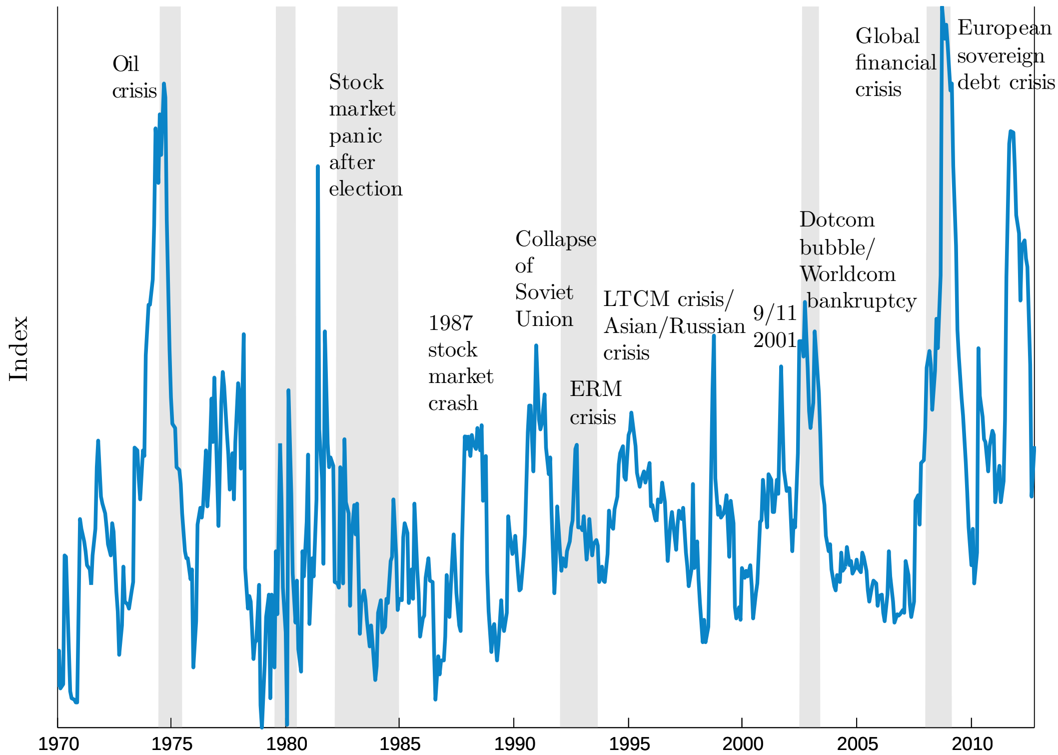
Financial variable	λ_i
Banking sector volatility	0.8572
TED spread	0.6966
Historical volatility of the CAC	0.6101
β of the banking sector	0.4726
Expected bank lending	0.4389
Corporate credit spread	0.4308
Exchange rate volatility	0.3851
Consumer credit spread	0.3782
Housing credit spread	0.2851
Credit default swaps on corporate sector	0.2102
Credit default swaps on banking sector	0.1135
Credit default swaps on government bonds	0.1093
Money market spread	0.0989
Term spread	0.0582
Government bond spread	-0.0652
CAC 40 log-returns	-0.7945
Banking sector equity index	-0.9079

Notes: The values are extracted from the loading matrix Λ of the DFM.

3 A financial stress index for France

After estimating the model, we obtain a single composite financial stress index for France (Figure 4). The first incident to which the FSI strongly reacts is the OPEC oil embargo from October 1973 to March 1974, when France entered into a recession. Even if France was relatively little exposed to the embargo due to its specific foreign policy, it was significantly hit by an increase in oil prices and rising commodity prices. Soaring import prices led to sharply increasing production costs for the French industry. Splitting up the index into the three subgroups indicates that mainly the indicators from the banking sector and from the capital market contributed to the stress on financial markets (Figure 5). Nominal exchange rate volatility slightly increased.

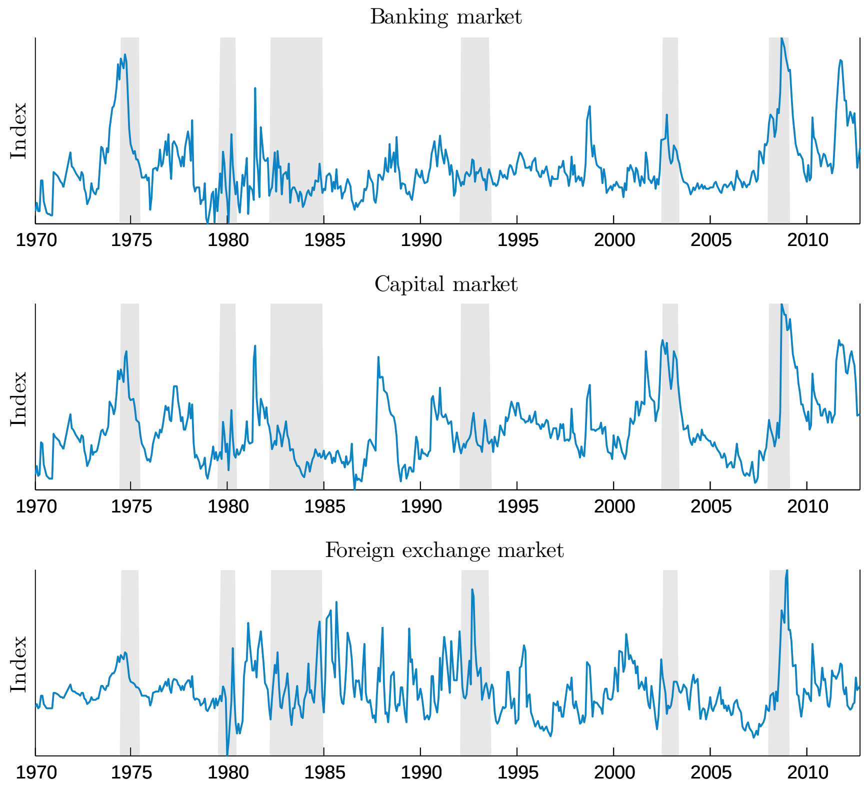
Figure 4: *Financial stress index for France*



Notes: The index is calculated on the basis of 17 financial market variables using a dynamic approximate factor model. Shaded areas indicate recessions using calculations by the Economic Cycles Research Institute.

The next peak of the FSI depicts the largest drop in stock market returns since

Figure 5: *Contributions of subgroups to the FSI*



Notes: Shaded areas refer to recession dates provided by the Economic Cycle Research Institute.

the Second World War. It occurred after the presidential election of François Mitterrand on May 10, 1981. On May 13, 1981, when the left wing released the list of the companies to be nationalized, it induced a panic on the French stock market with a one-day decline of -15.1%. The day after, the volatility reached its highest level of 94.3%. The FSI fairly reproduces this stress on stock markets and peaks only slightly below the level reached during the oil embargo. Figure 5 confirms that the large part of the FSI increase came from capital markets (especially stock returns and stock market volatility) and the banking sector (money market spread), while exchange rate volatility remained rather subdued.

On October 19, 1987, the French stock market collapsed once again, reacting to the events happening on stock markets in the United States on "Black Monday". The stock market index successively declined until it reached its lowest level in January 1988. At that time, the stock market index lost approximately 40% of its capitalization. Three years later, on August 19, 1991, the Soviet coup d'état attempt against President Mikhail Gorbachov led to high political uncertainty in France given the post-Cold War context.

On July, 22 1992, the European exchange rate mechanism was under attack; indeed, the exchange rate bands widened so much that central banks had to intervene to stop devaluation in countries like France and support the French franc. On October, 2 1992, the Bank of France spent 80 billion franc to support its currency. The FSI also strongly reacts to this event. Figure 5 fairly depicts that the increases in the FSI were mainly driven by higher exchange rate volatility while the sub-indexes of the banking sector and the capital market do not rise significantly, since other market segments were not strongly affected. This is the reason that the effect of the ERM crisis did not have a large effect on the FSI: it peaks far below the other events in French history.

The next significant increase in the FSI depicts the events associated to the Asian and Russian crisis as well as the default of the large hedge fund Long Term Capital Management (LTCM) in 1998. The French banking sector was significantly affected by this financial market turmoil. The bank volatility index was the main driver of increases in financial stress, reaching the highest value since its first registered value in 1986.

From 1998 until 2001, financial stress dropped to very low levels. Investors perceived the introduction of the euro as a positive sign for France such that stock markets dynamically increased and government bond spreads decreased further. The stock market rally was interrupted with the attacks on the world trade center on September 11, 2001. Afterward, stock markets recovered quickly before the worldwide stock market downturn of 2002.[7]

The highest peak of the FSI occurred before the financial crisis 2008/2009, after the collapse of the investment bank Lehman Brothers in September 2008. All three subgroups of the FSI indicate large increases in financial stress. The

[7]Stock markets across the United States, the United Kingdom, Canada, Asia and all over Europe slid persistently reaching troughs last recorded in 1997 and 1998.

second largest drop in French stock market returns in history occurred on October 6, 2008, when a panic effect related to the stability of the financial sector spread throughout Europe, inducing a dramatic one-day decline of -9.5% of the CAC. When the US stock market plunged on October 15, 2008, French volatility hit its second highest level at 92.5% the following day. In this context, after accumulating bad news, the FSI reached its highest level in November 2008. As a comparison, the highest level of historical (implied) volatility of the French stock market since 1982 occurred on October, 16 2008 at 92.7%. In addition, the highest exchange rate volatility level since 1982 occurred on December 22, 2008 at 29%.

As an economic response to the financial crisis, the French government announced a 26 billion Euro stimulus plan on December 2008 to stabilize the economy, anticipating the drastic fall in aggregate demand which in the end resulted in the worst recession since 1945. At the end of 2010, this stimulus package was increased to 38.8 billion Euro. On the one hand, this policy may have contributed in a decline of the stress index at the beginning of April 2009, the month that corresponds approximately to the end of the recession in France. On the other hand, it rapidly increased the government's debt-to-GDP ratio putting at stake fiscal solvency. As a result, rating agencies began downgrading various countries, pushing their sovereign yields up. In May 2010, the FSI peaked locally, when money markets almost dried out and the European financial system was under strain. In reaction to this, the ECB intervened on capital markets through bond purchases to reduce the interest rate levels of sovereign borrowers. Subsequently, the perception of the crisis gravity diminished temporarily. In particular, the French economy has been relatively resilient to investors uncertainty and did not suffer from a large confidence loss like other peripheral countries such as Spain and Italy.

From August 2011 to January 2012 when market concerns of contagion effects on other countries in the euro area came up, the FSI increased sharply. In particular, investors attributed higher default risks to Spain's and Italy's debts, which partly contaminated the credit spread of French corporations and the government. In addition, investors became uncertain about the future design of the European monetary union (due to delays in the implementation of the European

Stability Mechanism, general policy uncertainty, and the possible exit of Greece). This spillover effect to the French economy was quite pronounced for two reasons. France contributes about 20% to the European Financial Stability Facility with a maximum guarantee of 110 billion Euros, which means that it bears a fifth of a potential bail out. Second, French banks are the most exposed to peripheral countries; indeed, US money-market funds have cut their lending to French banks because they may experiment problems of contagion from the peripheral countries. Consequently, the banking sector index declined from 1026 points on January 2007 to 235 points in January 2012. The volatility of the French banking sector peaked at 121% in November, 2 2011. With the announcement of ECB's Long Term Refinancing Operations to loan 489 billion Euros to European banks for three years, the FSI has begun to shift downward since early 2012. The FSI has decreased further with the launch of the Outright Monetary Transactions (OMT) by the ECB on August, 2 2012.

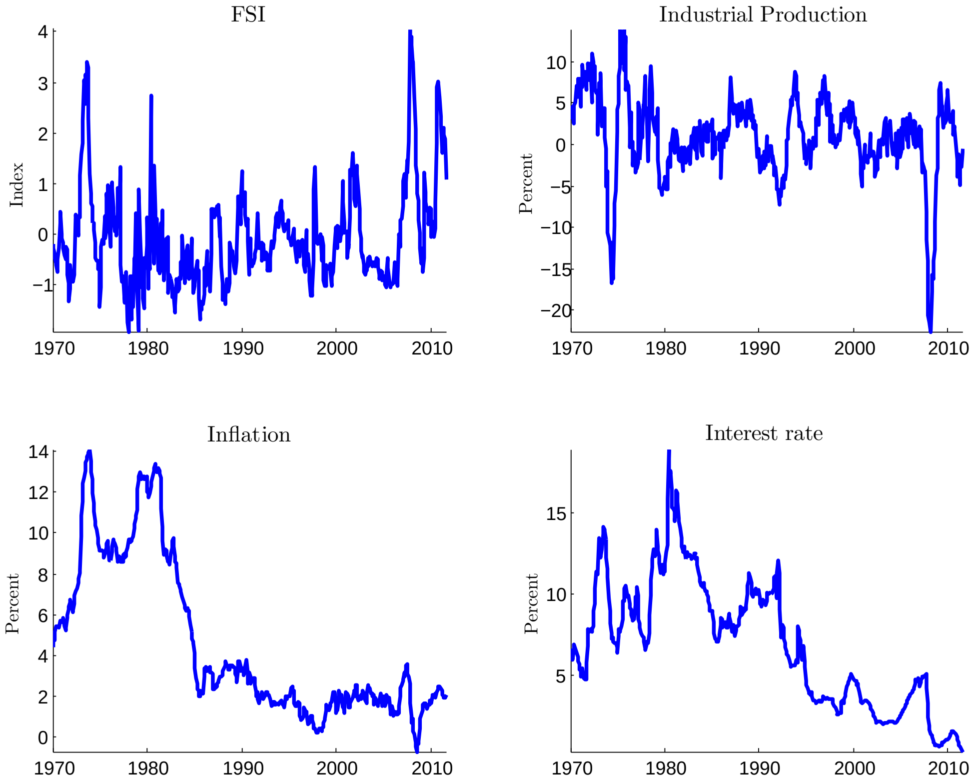
4 The FSI and economic activity

Typically, periods of high financial stress lead to a reduction in economic activity. This has been shown both theoretically and empirically for different countries. From the theoretical perspective, there are three different channels through which financial stress has effects on macroeconomic activity. First, in episodes of high financial stress, firms hesitate to invest or are reluctant to hire new workers. This effect is sometimes called the "wait-and-see effect" (Bloom (2009)). Second, banks are more cautious to lend because they increase credit standards (Bonciani and van Roye (2013)). This channel can be summarized as a loan supply effect. Third, high financial stress leads to higher funding costs of the private sector due to higher interest rate spreads and rising liquidity premia (Gilchrist and Zakrajsek (2012)). The negative impact of high financial stress episodes has also been shown empirically for different countries (see Bloom (2009), Baker et al. (2012), Hakkio and Keeton (2009), Holló et al. (2012), and van Roye (2013), among others, and Kliesen and Smith (2010) for a survey). Beside its purpose for financial stability monitoring, the usefulness of the French FSI crucially depends on its ability to relate financial market developments to economic activity. Therefore, we will test the FSI on its statistical properties and its relationship to economic activity in France.

A Markov-Switching Bayesian Vector Autoregressive Model

First, we will identify periods of high financial stress and those of low financial stress. To do so, we have to assume that the properties of FSI are state dependent. Because financial instability can be considered a tail event, we assume two regimes a priori. In particular, we assume that financial stress occurs suddenly and stochastically with a certain persistence within either regime. We apply a Markov-Switching Bayesian Vector Autoregressive model (MSBVAR) model to identify the regimes, i.e., low-stress and high-stress regimes. The Markov-Switching setup is particularly useful in a nonlinear environment because it can identify sudden behavioral changes of financial variables. In particular, we use the MSBVAR model developed by Sims et al. (2008). Therefore, our analysis is comparable to that of Hubrich and Tetlow (2012), who analyze the impact of financial stress on the US economy. We set up the model with four endogenous variables: the financial stress index, the inflation rate, industrial production growth and the short-term interest rate, i.e., the 3-month PIBOR/EURIBOR (Figure 6).

Figure 6: *Variables included in the MSBVAR*



The endogenous vector of the model is given by $y_t = [FSI_t \quad \Delta IP_t \quad \pi_t \quad i_t]$. We follow Sims et al. (2008) and set up a MSBVAR as follows:

$$y_t' A_0(s_t) = \sum_{i=1}^{\rho} y_{t-i}' A_i(s_t) + z_t' C(s_t) + \varepsilon_t' \Theta^{-1}(s_t), \ t = 1, \ldots, T, \tag{15}$$

where y_t is the 4-dimensional column vector of endogenous variables, A_0 is a non-singular 4×4 matrix and $A_i(k)$ is a 4×4 matrix for $1 \leq k \leq h$, s_t are unobserved states at time t, and ρ is the lag length. and $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$ is an n-dimensional shock process. In our case, we assume two states $s_t = 1, 2$. Furthermore, z_t is an indicator matrix taking the value 1, representing a column vector of constants. $C(s_t)$ is an $m \times n$ intercept matrix for $1 \leq k \leq h$, and Θ is an $m \times n$ diagonal matrix of factor loadings scaling the stochastic volatility factors on the vector of unobserved shocks ε_t. The structural shocks ε_t are normal with mean and variance equal to the following:

$$\mathbb{E}[\varepsilon_t|Y_1, ..., Y_{t-1}, z_1, \ldots, z_{t-1}] = 0, \tag{16}$$

$$\mathbb{E}[\varepsilon_t \varepsilon(t)'|y_1, \ldots, y_{t-1}, z_1, , \ldots, z_{t-1}] = I_n, \tag{17}$$

Defining the initial conditions $x_t = [y_{t-1}, \ldots, y_{t-\rho}, z_t]'$ and $F(s_t) = [A_1(s_t)', \ldots, A_\rho(s_t)', C(s_t)]'$, the model can be written in compact form:

$$y_t' A(s_t) = x_t' F(s_t) + \varepsilon_t' \Theta^{-1}(s_t), \forall\ 1 \leq t \leq T, \tag{18}$$

Finally, assuming conditionally normal structural disturbances: $\varepsilon_t'|Y^{t-1} \sim \mathcal{N}(0, I_n)$, where $Y^t = \{y_0, \ldots, y_t\}$ we can write the model in reduced form:

$$y_t' = x_t' B(s_t) + u'(s_t), \tag{19}$$

where

$$B(s_t) = F(s_t) A^{-1}(s_t), \tag{20}$$

and

$$u(s_t) = A'^{-1}(s_t) \epsilon_t' \Theta(s_t), \tag{21}$$

The regime change is determined by a first-order Markov process. The Markov chain has the following probability rule: $\mathcal{P}(S_t = j|s_{t-1} = i) = p_{ij}$, where $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$. This implies that the current regime s_t only depends on the regime one period before. The model's parameters $\hat{\theta} = (\hat{\phi}_1, \hat{\phi}_2)$ depend on the unobservable regimes in a nonlinear manner. Like Sims et al. (2008), we apply Bayesian techniques to estimate the model's parameters.

Prior selection As in all Bayesian models, the priors have to be chosen carefully because the results crucially depend on them. Along with the priors we have to select for the parameters in the reduced-form BVAR, we also have to impose priors on the transition matrix. We choose priors very similar to those chosen by Sims et al. (2008) and Hubrich and Tetlow (2012) that are appropriate for a monthly model. We set the overall tightness for the matrices A and F to 0.6. The relative tightness of the matrix F is set to 0.15, whereas the relative tightness of the constant term is chosen to be 0.1. The Dirichlet priors are set to 5.6 for both the variances and coefficients. All parameters are presented in the table below.

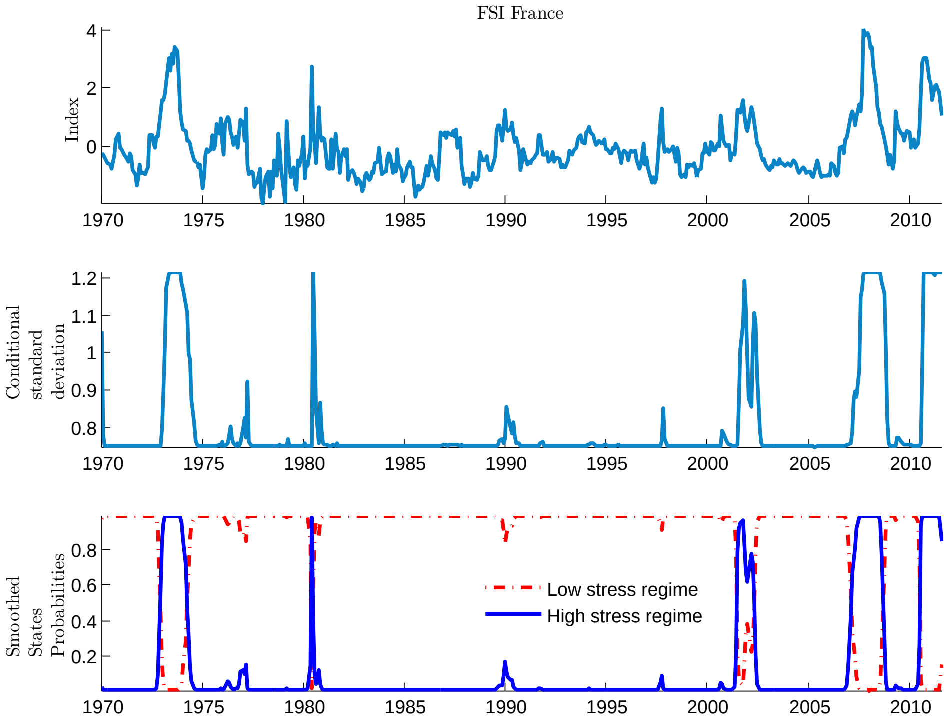
Table 2: *Prior selection for hyperparameters*

Type of prior	Value
Overall tightness for A and F	0.57
Relative tightness for F	0.13
Relative tightness for the constant term	0.1
Tightness on lag decay	1.2
Weight on nvars sums of coefficients dummy observations	10
Weight on single dummy initial observation including constant	10

Notes: Priors are selected based on Sims et al. (2008) and Hubrich and Tetlow (2012).

We use monthly data that range from 1971M1 to 2012M8, which leaves us 488 data points for each time series. To identify the BVAR model, we apply a lower triangle Choleski-decomposition of $A(s_t)$. In figure 7, the FSI, its conditional standard deviation and the smoothed state probabilities are depicted over time. The model indicates that the probability is very high that the French economy was in a high-stress regime during the oil crisis, the 1982 recession, the burst of the dotcom bubble, the recent global financial crisis and the European sovereign debt crisis.

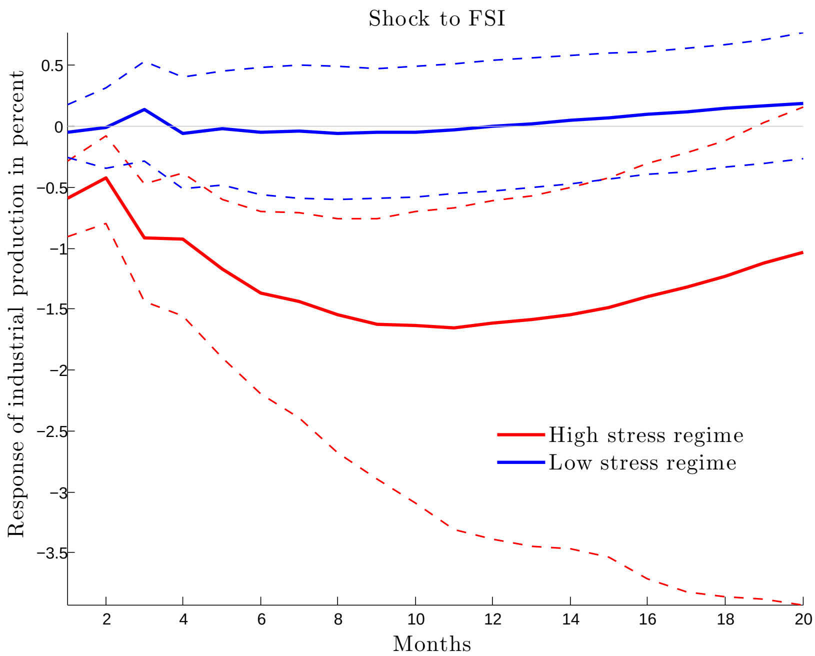
Figure 7: *Markov-Switching model FSI France*



Notes: The regime probabilities are illustrated in the lower panel.

In figure 8, we present the impulse response functions for the change in industrial production to a shock in the financial stress index. The feedback of financial stress differs considerably between regimes. While there is no significant change in industrial production in response to a financial stress shock in a low-stress regime, the shock in financial stress has great and persistent negative effects on industrial production in a high-stress regime. This finding is in line with studies for other countries and highlights the importance of nonlinearities in a crisis situation.

Figure 8: *Impulse response functions: BVAR model*



NOTES: Error bands are 10% on each side generated by Monte-Carlo with 500 replications.

5 Conclusion

In recent years, several papers have found a negative relationship between financial stress and economic activity. This study complements these papers by offering a useful financial stress index that is available in real time and is constructed using a sophisticated modeling approach. More precisely, in this chapter, we construct a financial stress index (FSI) for France that can be used in real time to evaluate financial stability in the French financial system. We construct the index using 17 financial variables. From these variables, we extract a common stress component using a dynamic approximate factor model. The model is estimated with a combined maximum-likelihood and Expectation Maximization algorithm, allowing for mixed frequencies and an arbitrary pattern of missing data. Subsequently, we test how the index relates to economic activity. Against this background, we set up a Markov-Switching Bayesian Vector Autoregressive Model (MSBVAR). In particular, we impose two regimes on the model, one low-stress and one high-stress regime, and analyze whether the transmission of financial stress on economic activity depends on the respective state.

The financial stress index fairly indicates important events in French history. It soars when liquidity premia, risk spreads and uncertainty measures increase sharply. Therefore, the index can capture systemic events when a batch of indicators shows signs of financial market tensions.

We find evidence that one regime is not sufficient to model economic activity within this model setup. A two-regime model delivers results that are significantly more appropriate and are able to capture the nonlinearities in the model. Furthermore, the estimation results indicate that financial stress transmits very strongly to economic activity when the economy is in a high-stress regime, whereas economic activity remains nearly unaltered in a low-stress regime. These findings are robust across different identification schemes within the BVAR model.

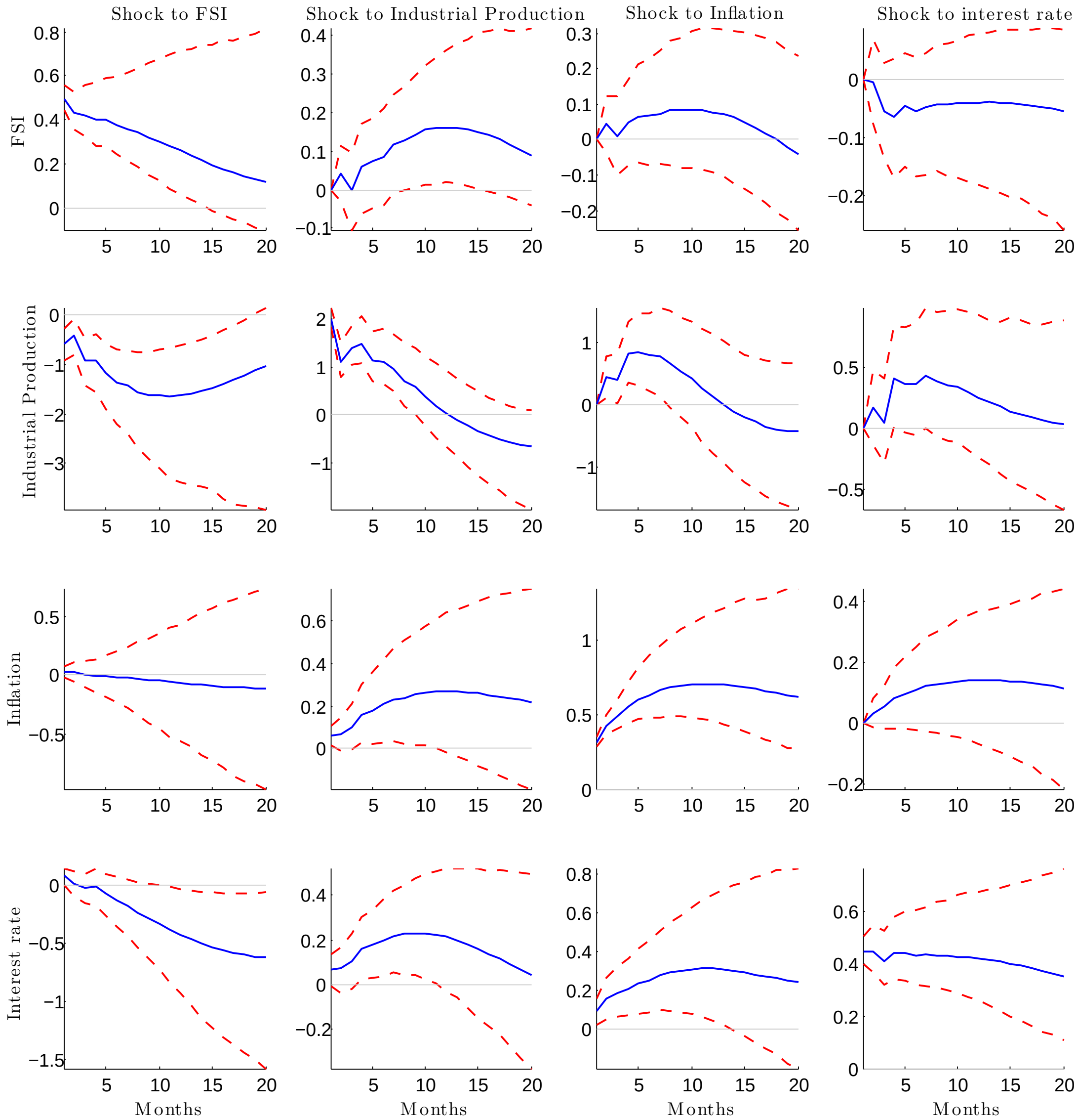
A Appendix

Table A1: *Data description*

Indicators	Native frequency	First observation
Banking indicators		
TED-spread	monthly	1973M01
Money market spread	daily	1999M01
β of banking sector	daily	1980M03
Banking sector equity index	daily	1986M06
Expected Lending	quarterly	2003M01
CDS on banking sector	monthly	2007M01
Banking sector volatility	daily	1986M06
Capital market indicators		
Term spread	monthly	1976M01
Corporate credit spread	monthly	2003M01
Housing credit spread	monthly	1990M01
Consumer credit spread	monthly	2003M01
CAC 40 log-returns	daily	1970M01
Stock market historical volatility	daily	1970M01
Government bonds spread	daily	1987M12
CDS on corporate sector	monthly	2008M01
CDS on 10Y government bonds	daily	2007M12
Foreign exchange indicators		
Nominal synthetic exchange rate volatility	daily	1980M01

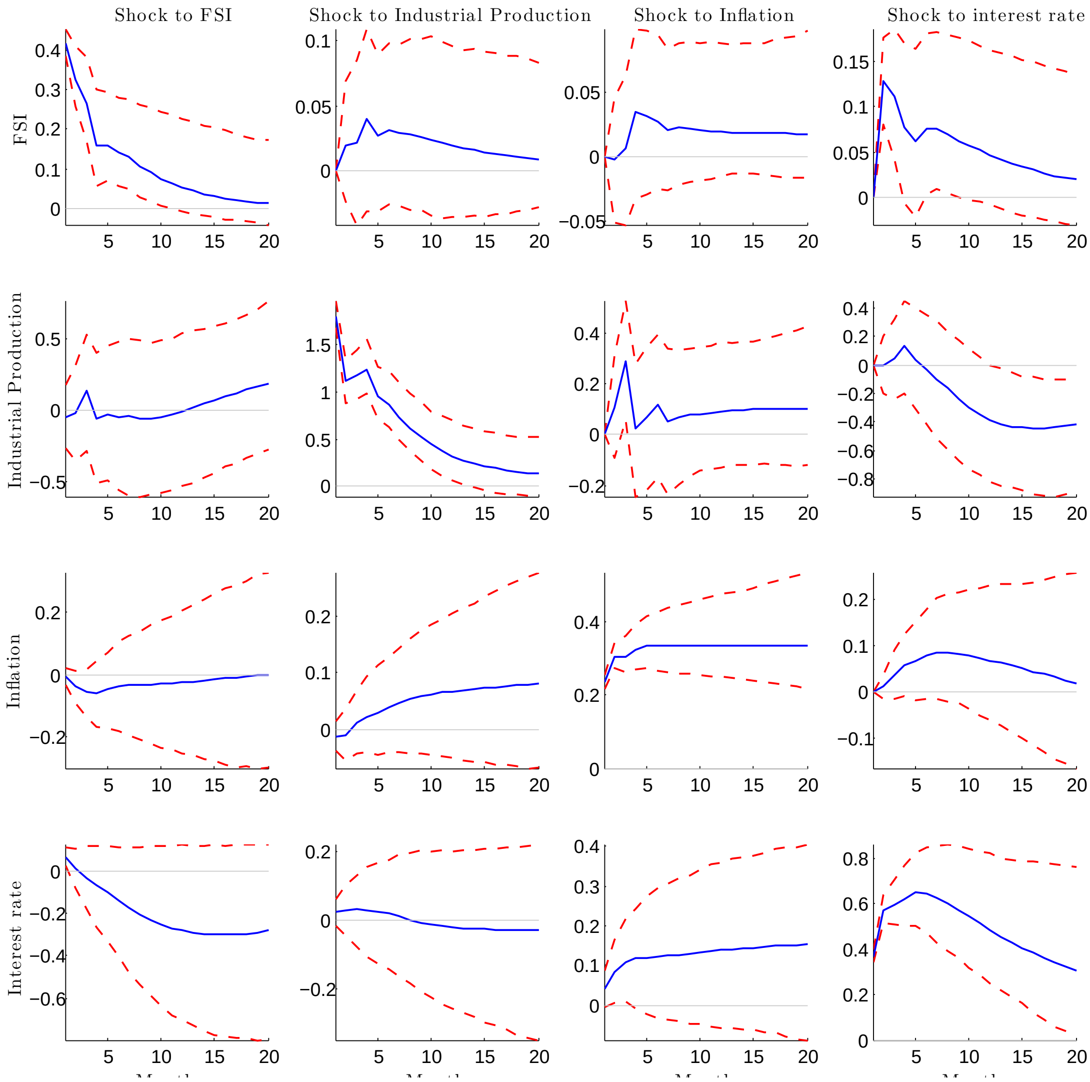
Source: European Central Bank, Banque de France, Thomson Financial Datastream, own calculations.

Figure A1: *Impulse response functions: high-stress regime*



Notes: Error bands are 66% bands generated by Monte-Carlo with 500 replications.

Figure A2: *Impulse response functions: low-stress regime*



NOTES: Error bands are 66% bands generated by Monte-Carlo with 500 replications.

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