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Fiscal policies, Output Growth and Financial Stress Regimes: A Threshold VAR Approach

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Chapter 1

Introduction

The Covid-19 pandemic which unfolded worldwide, turned a localized shock in China into a significant global shock at economic level leading to a severe downturn of the world economy. In response to the subsequent recession, monetary policies prevented the pandemic crisis from morphing into a financial crisis as well as unprecedented fiscal stimulus packages have been introduced in order to prevent the crisis from spiraling. However, evidence shows that economic downturns are often associated with periods of financial stress or even with financial crisis as in the Global Financial Crisis. Indeed, since 2008, financial stress has gained an increased popularity among macroeconomists, who turned their attention to the spillover effects of financial stress on the real economy as well as to their interplay with fiscal policy. In particular, during periods of economic downturn or stress in financial markets the effects of fiscal developments on economic activity might be different from what is usually observed in good or normal times, namely the size of fiscal multipliers could change according to the state of financial markets. This means that financial stress can act as a non-linear propagator of fiscal shocks on output growth.

In a theoretical framework, the relation between financial instability and economic policy can be two-sided. On the one hand, irrespectively of the causes of financial instability, policy makers may try to soften its effect on the economy. On the other hand, so-called “bad” policies can also contribute to financial instability. For instance, a situation of large government indebtedness might cause a loss of confidence in the ability of the government to pay back orderly the outstanding stock of government debt. As a result, unsustainable fiscal policies undermine sovereign debt credibility and financial markets may refuse to buy new government debt and secondary market liquidity may decline. The reduced liquidity can weaken the balance sheet of the banks and other financial institutions that hold government debt. Balance sheet losses related to the price drops in government securities can affect negatively the lending capacities of the banks, which might reduce the credit flow to the private sector. Hence, it is relevant to examine whether and how the effects of fiscal developments on economic activity differ in times of financial instability, i.e. whether there are non-linearities at play and if fiscal multipliers are different.

For example, in empirical macroeconomic literature, past theoretical work by Christiano et al. (2009), Woodford (2010), Afonso et al. (2011), emphasize that government spending may have a larger multiplier during periods of financial stress, in the sense that fiscal policies should be more successful in stimulating output under those circumstances. Blanchard and Leigh (2013) argued that the fiscal consolidation plans released by many advanced economies following the GFC, produced stronger recessionary effects than forecasted, because the estimated fiscal multipliers did not take into account the dismal situation of the financial system (together with the zero lower bound constraining monetary policy and the deep slack in the economy).

The present study aims to extend current knowledge of potential nonlinear effects of fiscal policy on the economic activity especially during the Covid-19 pandemic. In fact, although the Covid-19 recession did not originate from financial markets, a quieter crisis has gained momentum in the financial sector triggering conditions of financial stress in most countries in 2020. For this reason, I believe that non-linearities in the transmission of financial stress in the economic activity materialized also during the Covid-19 pandemic, and therefore the effects of fiscal policy shocks on economic activity might differ depending on whether the economy is in the high or low financial stress regime. To address this issue, I conduct dynamic analysis to investigate whether and how: (i) positive fiscal shocks have a different impact on economic activity from negative shocks (asymmetries), (ii) fiscal policy shocks of different magnitudes have disproportionate effects (shock non-linearity), and (iii) the effects of fiscal developments on economic activity differ according to the state of the economy when the shock hits (regime-dependencies). Finally, I further investigate (iv) how important a fiscal shock is in explaining the variability of the economic activity, and (v) how that importance changes over time.

The analysis is conducted using a Threshold Vector Autoregression model (TVAR, Tsay, 1998) using quarterly data for Germany, Italy, U.K. and France, for the period 1997:1-2021:1. This model is useful to capture non-linear dynamics such as regime switching and asymmetric responses to shocks within a multi-equation framework encompassing endogenous macroeconomic, fiscal and financial variables. These are GDP growth (y), inflation (π), the fiscal variable (f), the short-term interest rate (i), and the indicator for financial market conditions (s), for which I have chosen the Country-Level Index of Financial Stress (CLIFS), developed by Duprey et al. (2015) for the ECB. The threshold variable is included in the model and its critical value is estimated endogenously. Therefore, a shock to the financial conditions index, as well as to any of the other variables in the model, can induce a switch in the regime. The analysis adapts Hansen's (1996) simulation methodology for proper estimation and inference of threshold effects. The TVAR is identified by means of a recursive identification scheme and dynamic analysis is conducted by computing generalized impulse-response functions (GIRFs) and generalized forecast error variance decompositions (GFEVDs) to allow for the scrutiny of regime-dependent responses and corresponding shocks' relative contributions. By doing so, I attempt to isolate the relative effects of fiscal policy shocks and shed a light on the debate of whether contractionary fiscal shocks have larger multipliers than expansionary shocks.

In this study, the contribution to the existing literature regarding fiscal policy analysis comprises two important innovations. First, the inclusion in the TVAR model of a country-specific measure representing financial instability, namely the Country-Level Index of Financial Stress (CLIFS), which is able to identify the financial stress periods associated with the recent Covid-19 recession. This would tell us whether and how the effects of fiscal developments on economic activity differed depending on financial market conditions also during the pandemic, which is an issue not investigated so far in macroeconomic literature. Second, I use a generalized version of the forecast error variance decomposition for multivariate nonlinear models (Lanne and Nyberg, 2016) computed based on generalized impulse response functions, in order to study the relative importance of fiscal shocks in explaining the variability of the economic activity, and how this importance changes over a reasonable forecast horizon, which is another issue not investigated so far in fiscal policy analysis.

The main results are the following: (i) the use of a nonlinear framework with regime switches, determined by a financial stress indicator, is corroborated by nonlinearity tests. Thus, there are reasons to believe that the data may present nonlinear dynamics and therefore our TVAR model may be the most adequate specification to describe the behavior of the DGP. (ii) In Germany and the U.K., differences in the estimated fiscal multipliers in the two regimes indicate that fiscal policy has larger effects on output growth in the high stress regime than in the low stress regime confirming the strong regime-dependencies of the DGP for these countries. The opposite is true for Italy and France, where the impact of fiscal policy in the low stress regime is much higher leading the economy to a switch to the high stress regime. (iii) positive fiscal shocks have a different impact on economic activity from negative shocks in Germany, Italy and France. In the U.K. these asymmetries are absent. (iv) In Germany (in the high stress regime), Italy (in the low stress regime) and France (in the low stress regime) disproportionate effects between small and large shocks materialize. On the other hand, one and two standard deviations shocks practically coincide in the U.K in both regimes. (v) fiscal policy shocks immediately decrease financial stress in all countries when the shock hits in both regimes, except in Italy (in the high stress regime), where fiscal shocks slightly increase financial stress. (vi) In Germany and in the U.K. fiscal shocks play a more important role when the economy is in the high stress regime because they contribute more to the variation of output growth. Furthermore, fiscal shocks are more important than shocks to the other variables in both regimes for the same reason. (vii) The relative contribution of fiscal shocks on output growth remains broadly constant over time with some exceptions.

The thesis is organized as follows. Chapter 2 reviews the literature on vector autoregressive models in macroeconomic and fiscal policy analysis. Chapter 3 explains the methodology. Chapter 4 describes the data and the variables involved in the model. Chapter 5 shows the empirical results, and chapter 6 concludes.

Chapter 2

Vector autoregressive models in macroeconomic and fiscal policy analysis: A literature review

2.1) Linear VAR models – 2.2) Linear VAR models in fiscal policy analysis - 2.3) Non-linearities within VAR analysis: disproportionality, asymmetry and initial conditions – 2.4) Non-linear regime-switching VAR models: The TVAR and the MSVAR – 2.5) Fiscal policy and financial instability - 2.6) Non-linear VAR models in fiscal policy analysis

2.1 Linear VAR models

Understanding and measuring the effects of both policy actions and other non-policy shocks has been, and still is, the centrepiece of the design and the implementation of sound economic policies and the creation of economic theories to describe the functioning of modern economies. What are the sources of economic fluctuations? What are the transmission mechanisms of monetary and fiscal policy shocks? What are the effects of financial disruptions? This is just a sample of questions which have attracted the attention of macroeconomists for many decades, and the answer to these questions still represents, nowadays, the number one priority in macroeconomic research. Research from the 1940s through the 1970s emphasized fiscal and monetary policy shocks, identified from large-scale econometric models or single equation analyses. These models which included hundreds of equations and variables were highly criticized for the following reasons. First, no attention was paid on modelling agents' expectations. In particular, the models were largely inconsistent with the new, at that time, and growing rational expectation paradigm. Second, model variables were ex-ante, arbitrarily and without any help of statistical models, categorized into exogenous and endogenous. Third, the models were full of arbitrary restrictions and assumptions about causal relationships among variables. However, the 1980s witnessed an important innovation that fundamentally changed the direction of the research. Sims' (1980a) paper "Macroeconomics and Reality" revolutionized the study of systems driven by random impulses for the first time by introducing vector autoregression (VAR) and structural vector autoregression (SVAR) models as an alternative to the traditional large-scale dynamic simultaneous equation models used in academic and policy work at the time.

A VAR is an n-equation, n-variable linear model in which each variable is in turn explained by its own lagged values, plus current and past values of the remaining n-1 variables. This simple framework is able to explain the time dependence and the inter-dependence of the model's variables in a systematic way in order to capture rich dynamics in multivariate time series. As Sims (1980) and others argued, VARs provide a coherent and credible approach to data description, forecasting, structural inference and policy analysis. VARs come in three varieties: reduced form, recursive and structural. A reduced form VAR expresses each variable as a linear function of its own past values, the past values of all other variables being considered and a serially uncorrelated error term. The error terms in these regressions are the "surprise" movements in the variables. If the different variables are correlated with each other, as they typically are in macroeconomic applications, then the error terms in the reduced form model will also be correlated across equations. A recursive VAR constructs the error terms in each regression equation to be uncorrelated with the error in the preceding equations. This is done by judiciously including some contemporaneous values as regressors. A structural VAR uses economic theory to sort out the contemporaneous links among the variables (Bernanke, 1986; Blanchard and Watson, 1986; Sims, 1986). Structural VARs require "identifying assumptions" that allow correlations to be interpreted causally.

Nowadays, structural vector autoregressive (SVAR) models continue to be the workhorse of empirical macroeconomics and finance. Such models have four main applications. First, they are used to study the average response of the model variables to a given one-time structural shock. Second, they allow the construction of forecast error variance decompositions that quantify the average contribution of a given structural shock to the variability of the data. Third, they can be used to provide historical decompositions that measure the cumulative contribution of each structural shock to the evolution of each variable over time. Historical decompositions are essential, for example, in understanding the genesis of recessions or of energy price spikes in the data (see, e.g., Edelstein and Kilian 2009). Finally, structural VAR models allow the construction of forecast scenarios conditional on hypothetical sequences of future structural shocks (see, e.g., Waggoner and Zha 1999; Baumeister and Kilian 2011).

2.2 Linear VAR models in fiscal policy analysis

VAR models have become the most popular tool for investigating the effects of monetary policy during the nineties, and a number of stylized facts have been broadly identified. In response to a contractionary shock in the short-term interest rate, (i) real GDP declines with a hump-shape pattern, with a maximum decline occurring between one and one and half year, (ii) the price level declines persistently, and (iii) there is evidence for a strong liquidity effect, that is, the non-borrowed reserves drop in response to an increase of interest rates. A summary of the research in this field can be found in Christiano, et al. (1999).

However, no such broad consensus has emerged from the research on the effects of fiscal policy, notably regarding the qualitative responses of macroeconomic aggregates to changes in government expenditures or revenues. In this context, the main difficulties come from the approaches used to identify the changes in fiscal policy, since both government expenditures and revenues, to some extent, automatically respond to fluctuations in economic activity and thus these fluctuations need to be distinguished from deliberate policy changes. It is possible to separate these effects using estimated elasticities of tax revenues and government expenditures on output developments or to use external information such as the expected contemporary effects of the fiscal variables.

Nevertheless, the differences in the identification schemes in the VAR analysis often lead to different results. For instance, van Brusselen (2010) provides a broad overview of the effectiveness of fiscal policy, and an evaluation of fiscal multipliers notably in several VAR models. Caldara and Kamps (2008) compared the four existing approaches to identify fiscal policy shocks in VAR models using a dataset for the United States: (i) the Structural Vector Autoregression (SVAR) following Blanchard and Perotti (2002) and Perotti (2005) with calibrated sizes of the automatic stabilizers, (ii) the recursive identification scheme with the Choleski decomposition, (iii) the sign-restriction approach proposed for the analysis of monetary policy by Uhlig (2005) and applied by Mountford and Uhlig (2009), and (iv) the so called “narrative approach” assigning dummy variables associated with periods that are known for exogenous changes in fiscal policy, related to the increases in military build-ups. The authors argue that different identification and calibration schemes lead to similar results as far as the effect of government expenditures is concerned, e.g. the shock to government expenditures is likely to increase output. However, results are rather diverging regarding the responses to changes in taxes.

Romer and Romer (2007) applied a narrative approach in a similar fashion as they did in their 1989 paper on monetary policy. They went through the Congressional records and presidential speeches to identify both timing and size of the changes in taxation. Based on this identification, they find that tax increases were highly contractionary with multipliers that reached the value of three. This value is much higher than the values obtained from other VARs which are concentrated around one. Such discrepancy was explained by Favero and Giavazzi (2009) who argued that the results of Romer and Romer are caused by their estimation method based on one equation. After using the shocks by Romer and Romer within a multivariate framework, Favero and Giavazzi obtained results similar to those from traditional fiscal VARs.

The fiscal VAR approach based either on the SVAR or on the recursive identification was applied for several countries namely in the European Union. Aarle et al. (2003) estimated the effects of fiscal and monetary policy for the members of the European Monetary Union and found significant differences in reactions among the individual countries of the EMU. Muscatelli et al. (2002) found a significant decrease in the responsiveness of the fiscal policy variables in the U.S. since 1979, and similar decreases were also reported for Italy, Germany, France and the U.K.

For Germany, Heppke-Falk et al. (2006), using a VAR approach, mention that government expenditure shocks increase output and private consumption on impact with low statistical significance, while they decrease insignificantly private investment. They also found for government investment – in contrast to government consumption – a positive output effect, which is statistically significant until 12 quarters ahead. In addition, anticipated expenditure shocks have significant effects on output when the shock is realized, but not in the period of anticipation. The authors claim that the effects of expenditure shocks are only short-lived in Germany and government net revenue shocks do not affect output with statistical significance. However, they provide evidence that direct taxes lower output significantly, while small indirect tax revenue shocks have little effect. Moreover, the compensation of public sector employees is equally not effective in stimulating the economy.

For Italy, Giordano et al. (2007), also within a VAR framework, found that a shock to government purchases of goods and services has a sizeable and robust effect on economic activity: an exogenous 1% (in terms of private GDP) shock increases private real GDP by 0.6% after 3 quarters. The response declines to zero after two years, reflecting with a lag the low persistence of the shock. The authors also mention that the effects on employment, private consumption and investment are positive for Italy. In contrast, changes of public sector wages have no significant effect on output, while the effects on employment turn negative after two quarters. Shocks to net revenue were found to have negligible effects on all the variables.

The baseline specification was subsequently extended for an analysis of the impact of exchange rate (Monacelli and Perotti, 2006) and for government debt (Favero and Giavazzi, 2007 and Afonso and Sousa, 2009). Afonso and Sousa (2009a, b) used quarterly fiscal data from the U.S., the U.K., Germany and Italy along with the feedback from government debt, and also included the effects on asset markets in a Bayesian VAR model. For instance, Afonso and Sousa (2009b) using a Bayesian SVAR model provide some evidence that the government spending shocks have, inter alia, in general a small effect on GDP; do not impact significantly on private consumption and have a negative effect on private investment in the U.S., U.K., Germany and Italy. On the contrary, they found that government revenue shocks: have a positive (although) lagged effects on GDP and private investment. Interestingly, they found that when the debt dynamics is explicitly taken into account, (long-term) interest rates and GDP become more responsive and the effects of fiscal policy on these variables also become more persistent. Moreover, the results from Afonso and Sousa (2009b) also provide weak evidence of stabilizing effects of the debt level on the primary budget balance. They also find that government spending shocks, in general, have a positive, but small effect on GDP and also uncover a crowding out effect, which is present in all four countries.

Regarding the possibility of negative fiscal spending multipliers, and the so-called non-Keynesian effects of fiscal policy, several authors have argued along those lines. For instance, Alesina and Perotti (1996), Giavazzi and Pagano (1998, 2005), and Mitra (2006) mention that high government debt implies additional fiscal stress and a higher probability of higher taxes in the future. Therefore, higher private savings may arise and lower output, and thus the effects of increased government expenditure on output might be negative. In addition, there is also some evidence of expansionary fiscal contractions, the most prominent examples are Denmark in 1993-1985 and Ireland in 1985-1988, and Rzonca and Cizkowitz (2005) identified a similar pattern in the Central and Eastern European countries that have entered the EU in 2004-2006. However, Afonso (2010) reports that the empirical evidence for the EU countries is quite diverse in this respect, notably with alternative definitions of fiscal consolidation episodes.

2.3 Non-linearities within VAR analysis: disproportionality, asymmetry and initial conditions

Within the VAR framework, conventional vector autoregressive models are used to capture the linear dependence among multiple time series, but they might be unable to capture certain effects if these only materialize under particular circumstances. Indeed, non-linearities could be one of the reasons why these effects arise, and, for this reason, theoretical work in macroeconomics relies increasingly on specifying highly non-linear models. The corollary applies to theoretical models where higher-order approximations and global solutions are increasingly used in order to account for important dynamics which would be neglected in linear, first-order approximations. This issue is particularly relevant for the literature on financial accelerators which is a standard ingredient in business cycle models, but whose empirical validation falls short of its wide-spread use.

Capturing non-linearities in empirical research is thus a challenging exercise as the development of the theoretical literature has shown. Two main questions can be addressed by non-linear time series models. First, one can study differences in the characteristics of shocks. In this respect, different shocks can affect macroeconomic variables disproportionally. Shocks can differ with regards to their direction (positive vs. negative shocks) as well as to their size (small vs. large shocks).

Second, non-linearities can arise due to differences in initial conditions (regime-dependencies) that describe the point of the business cycle at which the economy is situated when a shock hits. It is not hard to imagine that certain shocks trigger effects that change depending on whether the shock is large or small. If the system is characterized by non-linearity, one would then expect disproportionate effects as a response to shocks of different magnitudes. Equivalently, the direction of a shock will lead to asymmetric effects if non-linearity is present. Most importantly, these mechanisms can operate to a different extent depending on whether the economy is very vulnerable or not at the time when the shock hits. Thus, in contrast to linear models, initial conditions can lead to a heterogeneous propagation of shocks, in the sense that they serve as an amplification (or attenuation) mechanism of shocks. For example, adverse shocks can have a more detrimental impact when the economy is vulnerable. Conversely, one could imagine that reactions of macroeconomic variables are muted when these are away from their steady state due to a higher degree of inertia of those variables that have already taken on extreme values.

Non-linearities also matter for impulse response analysis. Impulse response functions (IRFs) are essentially counterfactual forecasts whose accuracy can be expected to decline as the forecast horizon increases. Most VARs assume the structure of the multivariate system to be linear. As pointed out by Jordà (2005), a crucial question thus is if a linear VAR is an appropriate approximation of the true data-generating process (DGP). If this is not the case, misspecification will produce incorrect forecasts and results from IRF analysis will consequently be of little use. It will be shown below that non-linear VARs are appropriate tools to capture this conditionality.

2.4 Non-linear VAR models: The TVAR and the MSVAR

There is substantial interest in modelling the dynamic behaviour of macroeconomic and financial quantities observed over time. A challenge for this analysis is that these time series likely undergo changes in their behaviour over reasonably long sample periods. This change may occur in the form of a "structural break", in which there is a shift in the behaviour of the time series due to some permanent change in the economy's structure. Alternatively, the change in behaviour might be temporary, as in the case of wars or "pathological" macroeconomic episodes such as economic depressions, hyperinflations, financial crises or pandemics. For these reasons, the behaviour of economic variables might vary dramatically in business cycle expansions vs. recessions.

The potential for shifts in the behaviour of economic time series means that constant parameter time series models might be inadequate for describing their evolution. As a result, recent decades have seen extensive interest in econometric models designed to incorporate parameter variation. One approach to describing this variation, denoted as “regime-switching” model in the following, is to allow the parameters of the model to take on different values in each of some fixed number of regimes, where, in general, the regime in operation at any point in time is unobserved by the econometrician. However, the process that determines the arrival of new regimes is assumed known and is incorporated into the stochastic structure of the model. This allows the econometrician to draw inference about the regime that is in operation at any point in time, as well as to form forecasts of which regimes are most likely in the future.

Application of regime-switching models are usually motivated by economic phenomena that appear to involve cycling between recurrent regimes. For example, regime-switching models have been used to investigate the cycling of the economy between business cycle phases (expansion and recession), “bull” and “bear” markets in equity returns, and high and low volatility regimes in asset prices. There are a number of formulations of regime-switching time-series models in the recent literature, which can be usefully divided into two broad approaches. The first regime-switching models arise from the observed behaviour of the level of an economic variable in relation to some threshold value. These “threshold” models were first introduced by Tong (1983) and then surveyed by Potter (1999). The second regime-switching models arise from the outcome of an unobserved, discrete, random variable, which is assumed to follow a Markov process. These models, commonly referred to as “Markov-switching” models, were introduced in econometrics by Goldfeld and Quandt (1973) and Cosslett and Lee (1985) and became popular for applied work following the seminal contribution of Hamilton (1989). Hamilton and Raj (2002) and Hamilton (2005a) provide surveys of Markov-switching models, while Hamilton (1994) and Kim and Nelson (1999a) provide textbook treatments.

The Threshold VAR model. A threshold VAR model (Hubrich and Teräsvirta 2013; Tsay 1998) is a non-linear multivariate system of equations that models non-linearity additively and can consequently be estimated by OLS. TVARs condition on the initial environment and approximate the non-linear DGP by several regime dependent DGPs which are by themselves linear. Each regime is defined by boundaries (equal to certain values of the threshold variable) and coefficients of the VAR system are specific to each regime.

The system of equations to be estimated for the reduced-form VAR with one threshold is:

$$Y_t = c^L + \Phi^L(L)Y_{t-1} + (c^H + \Phi^H(L)Y_{t-1})I[s_{t-d}, \gamma] + \varepsilon_t$$

where Y_t denotes a vector of endogenous variables, c^L and c^H are vectors of intercept terms in the low-stress and high-stress regime respectively, $\Phi^L(L) = \sum_{i=1}^{p} \Phi_i^L \, L^{i-1}$ and $\Phi^H(L) = \sum_{i=1}^{p} \Phi_i^H \, L^{i-1}$ are the (reduced-form) lag polynomial matrices in the low-stress and high-stress regime respectively, and ε_t is the vector of random disturbances. s_{t-d} is the threshold variable that determines the dynamics of Y_t in different regimes, with a possible lag d; γ is the threshold value at which the regime switching occurs; $I[.]$ is an indicator function that governs the regime switches and takes the value of 1 if the threshold variable s_{t-d} is greater than the threshold value γ, and zero otherwise.

The above TVAR models can be classified as a special case of more general regime-switching models such as Markov-switching VARs (MSVARs). Regime-switching models often impose exogenous switches, whilst Markov-switching models have been applied mostly to distinguish between periods of recessions and booms (Hamilton, 1989). However, the assumption that the latent state is exogenous is quite unrealistic in a business cycle context where endogenous movements can be expected to lead to regime-switches. Models with endogenous switching might thus be more appropriate to capture non-linear dynamics if, as often is the case, regimes are associated with recurring dichotomous, i.e. “good” and “bad”, states of the economy.

Empirical studies have used threshold models to explore the asymmetry of shocks and nonlinear relationship between variables in financial markets and data from the real and monetary economy. For instance, TVAR models are widely used to study the asymmetric effect of fiscal and monetary policies in different credit, interest rate and inflationary regimes (Balke 2000; Fazzari et al. 2015; Shen and Chiang 1999). Balke (2000), for example, studies the propagation of shocks to output growth, the Federal Funds rate, inflation and measures of credit conditions during “tight” and “normal” credit market conditions using a TVAR framework with two regimes. The results suggest that shocks have a larger effect on output in “tight” credit regimes and that contractionary monetary shocks are more effective than expansionary ones. A similar approach is followed by Calza and Souza (2006) to study the transmission of monetary shocks across two credit regimes in the EU area and by Li and St-Amant (2010) to evaluate the effect of financial stress conditions on monetary policy effectiveness in Canada.

Another important application of threshold models has been to study the business cycle. For example, Altissimo and Violante (2001) study the joint dynamics of US output and unemployment using a bivariate TVAR model for recessions and expansions. Here, the lagged feedback variable, which measures the depth of the recession, defines the regime. The resulting model is a VAR with a fixed number of lags when the economy is in expansion and a time varying lag order when the economy is in recession. The authors find that nonlinearities are statistically significant only for unemployment, but it transmits to output through cross-correlation. Further evidence on the usefulness of threshold models for analysing the business cycle can be found in Koop and Potter (1999), Peel and Speight (1998), Koop et al. (1996), and Potter (1995), amongst others.

Threshold models are also popular in financial markets studies to explore the asymmetric relation between variables. In particular, a common application of TAR models includes determining the threshold effect in price movements related to transaction cost (Yadav et al. 1994). The threshold autoregressive conditional heteroskedastic class of models has been applied to study the nonlinear effect in volatility processes (Rabemananjara and Zakoian 1993).

Finally, multivariate threshold models have been extensively used in studying the dynamics in stock prices, returns, volatilities, inflation and economic activity (Barnes 1999; Griffin et al. 2007; Huang et al. 2005; Li et al. 2015). Griffin et al. (2007), for example, study the joint dynamics of stock market turnover, returns and volatility in 46 countries using a TVAR model with two regimes that are separated by the sign of the past return. The authors conclude that small negative return shocks, rather than large ones, are the drivers for the decrease in turnover after a decrease in returns. Li et al. (2015) study the interaction between Shanghai and Shenzhen stock markets in a bivariate three regime TVAR model where the threshold variable is the average difference of the log returns between the two markets. Their results suggest that the strength of interaction between markets is regime dependent. In particular, the Shanghai market leads most of the time, except for the third regime, where both markets interact simultaneously. A detailed review of the application of threshold models in empirical economics can be found in Hansen (2011).

The Markov-switching VAR model. Markov switching models are a popular family of models that introduces time-variation in the parameters in the form of their state- or regime-specific values. Importantly, this time-variation is governed by a discrete-valued latent stochastic process with limited memory. More specifically, the current value of the state indicator is determined only by the value of the state indicator from the previous period, thus the Markov property, and the transition matrix. The latter characterizes the properties of the Markov process by determining with what probability each of the states can be visited next period, given the state in the current period. This setup decides on the two main advantages of the Markov switching models. Namely, the estimation of the probability of state occurrences in each of the sample periods by using filtering and smoothing methods and the estimation of the state-specific parameters. These two features open the possibility for improved interpretations of the parameters associated with specific regimes combined with the corresponding regime probabilities, as well as for improved forecasting performance based on persistent regimes and parameters characterizing them.

Markov switching models presume a finite number of regimes and exogeneity of the Markov process which is defined as its independence of the model unpredictable innovations. In many such applications, desired properties of the Markov switching model have been obtained either by imposing appropriate restrictions on transition probabilities or by introducing the time-dependence of these probabilities determined by explanatory variables or functions of the state indicator. One of the recent extensions of this basic specification includes Infinite Hidden Markov models that grant great flexibility and improved forecasting performance by allowing the number of states to go to infinity.

Unlike in TVAR models, in MSVARs, the state variable is generally not observed. MSVARs thus suffer from a lack of tractability of the underlying regime-switching process as the variable(s) which cause a regime-switch cannot be identified. In contrast, TVARs explicitly model the endogenous regime-switching process which is why they are also described as “self-exciting”. TVARs can therefore be viewed as a type of MSVARs with endogenous switching where the probability structure is modelled simplistically. TVARs have the advantage that the regime-switching is tractable, but also require the choice of a threshold variable in order to endogenize the regime-switching. Since the focus of this work is on the effect on output growth to fiscal policy shocks for generating non-linearities, country level financial stress indicator is considered as (endogenous) switching variable. The latter was chosen as switching variable as it constitutes the channel through which non-linearities could materialize.

In macroeconomic literature, Markov switching models have been used extensively in the business cycle literature to identify turning points and to ultimately date recessions. In particular, these models have been put forward in the literature on measuring financial market stress, linking it to different macroeconomic regimes. For example, Hollo et al. (2012) test the ability of a fixed transition probability MS model to fit the peaks of the euro area financial stress index, while Duprey et al. (2015) use a similar MS model to identify periods of financial market turmoil for each EU country. In the context of a MS-VAR model, Hartmann et al. (2013) show that the response of output to financial stress is much larger in case of a negative shock when allowing for regime switches.

2.5 Fiscal policy and financial instability

After the Global Financial Crisis of 2008, macroeconomic research began to focus on how fiscal multipliers vary with changes in economic conditions as well as the extent to which fiscal policy actions affect output growth depending on the different states of the economy. According to Afonso et al. (2011), this is because the effects of fiscal policy and the size of fiscal multipliers can differ in times of financial instability as in the GFC of 2008. This also links with the Keynesian-like story about countercyclical economic policy, and the possible positive impacts of fiscal stimuli. The idea is that the government steps in to compensate the decline in private sector demand in order to stabilize aggregate demand. Almunia et al. (2009), who compared the policies during the Great Depression and the 2008-09 crisis concluded that when fiscal policy was used in the 1930s it worked, while the evidence for the effectiveness of the monetary policy is rather mixed.

However, fiscal policy can also contribute to financial instability if, for instance, the issuance of substantial amounts of sovereign debt causes fiscal stress and a potential fiscal and/or financial crisis. In particular, unsustainable fiscal policies may undermine sovereign debt credibility and financial markets may refuse to buy new government debt, while transactions in the secondary market may also become less frequent. The inability to sell government bonds reduces its liquidity and weakens the balance sheet of the banks and of other financial institutions that hold government debt. The balance sheet losses related to the price drops in government debt securities negatively affect the lending capacities of the banks, which consequently might reduce the flow of credit to the private sector.

2.6 Non-linear VAR models in fiscal policy analysis

The literature dealing with the effects of fiscal policy during the periods of financial stress is relatively scarce but growing. Baldacci et al. (2008) tried to answer the question of whether fiscal policy might shorten the recession caused by banking crisis. Using OLS estimation and truncated Logit on a dataset containing 118 banking crises in 99 countries 1980-2000, they have found that fiscal policy responses are significant for the duration of the crisis, and that the composition of the fiscal package is a key to success. In this respect their results are in line with Blanchard et al. (2009) who tried to summarize the policy recommendations from the empirical literature in order to give guidelines for the construction of fiscal stimuli packages that had been prepared at that time.

Following the Keynesian argument, some studies suggested larger fiscal multipliers in recession, e.g. Fazzari, Morley, and Panovska (2015), Auerbach and Gorodnichenko (2012, 2013), and Barro and Redlick (2011). In addition, some researchers working in the New Keynesian DSGE framework argued that the large size of estimated fiscal multipliers was the consequence of the zero lower bound on interest rates, e.g. Coenen et al. (2012), Christiano, Eichenbaum, and Rebelo (2009), and Cogan et al. (2010). The existing literature has particularly focussed on the experience of the US economy; for example, Auerbach and Gorodnichenko (2012); Bachmann and Sims (2012); Ramey and Zubairy (2014). It is therefore interesting to investigate the extent to which the euro area experience together with the UK experience is consistent with this.

Using a TVAR model with a financial stress indicator as a threshold variable, Afonso et al. (2011) has shown that for the US, Germany, Italy and the UK, the responses of economic growth to a fiscal shock are mostly positive in both financial stress regimes, that financial stress has a negative effect on output growth and worsens the fiscal position, and that the nonlinearity in the response of output growth to a fiscal shock is mainly associated with different behaviour across regimes. Moreover, they found that the size of the fiscal multipliers is higher than average in the GFC. However, and as far as I can tell, there are no studies that investigate empirically the effects of fiscal developments within a multi-equation framework, that include the Covid-19 recession to the estimation sample, which also triggered, albeit for a small period, the financial stress indicator used in this work. And that is exactly what I do in this study.

Crafts and Mills (2013) estimate the government expenditure multiplier for interwar Britain (1919-1938) based on quarterly data. They find that the expenditure multiplier is less than one (between 0.3 and 0.8) depending on the model specification and the sample period. Rafiq (2014) finds larger government spending multipliers in recession than in expansion for UK data while using a small-scale Bayesian time-varying VAR model.

Chapter 3

Methodology

3.1) The benchmark VAR model – 3.2) The TVAR model - 3.3) – Testing nonlinearity – 3.4) Estimation technique - 3.5) Identification – 3.6) Linear impulse response functions - 3.7) Generalized impulse response functions – 3.8) Forecast error variance decompositions - 3.9) Generalized forecast error variance decompositions

3.1 The benchmark VAR model

The starting point of our analysis is a linear VAR model without exogenous variables, whose reduced form can be specified as:

$$Y_t = c + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \varepsilon_t \tag{1}$$

where Y_t is a (n x 1) vector of stationary endogenous variables included in the VAR (in our case n = 7), $Y_{t-1}, \dots, Y_{t-p}$ are (n x 1) vectors of the lagged values of the endogenous variables, c is a (n x 1) vector of constant terms, $\Phi_1, \dots, \Phi_p$ are (n x n) coefficient matrices, and ε_t is a (n x 1) vector of white noise disturbances with $E(\varepsilon_t) = 0$ and variance-covariance matrix $E(\varepsilon_t \varepsilon_t') = \sum_\varepsilon$. As the components of ε_t may be instantaneously correlated (i.e. the matrix $\sum_\varepsilon$ may not be diagonal), the impulse responses obtained from the reduced form model might not properly reflect the relationships between the variables. In order to consider a model with uncorrelated residuals, we can model the instantaneous relationships between variables directly by defining a structural VAR (SVAR) model in the A-B form[1]. Hence, I multiply both sides of equation (1) by the matrix A, which is a (n x n) matrix representing the structural contemporaneous relationships between the endogenous variables. If the reduced form disturbances are linear combinations of the structural shocks U_t in the form $\mathrm{A}\varepsilon_t = BU_t$, the SVAR model can be represented as:

$$\mathrm{A}Y_t = \bar{c} + \bar{\Phi}_1 Y_{t-1} + \bar{\Phi}_2 Y_{t-2} + \cdots + \bar{\Phi}_p Y_{t-p} + BU_t \tag{2}$$

[1] A detailed description and derivation of the A-B model, as well as the corresponding A and B models can be found in Amisano and Giannini (1997), Lutkepohl (2005) and Lutkepohl and Kratzig (2004). Further applications of the A-B model can be found in Pagan (1995), Breitung and Lutkepohl (2004) and Blanchard and Perotti (2002).

where Y_t is again a (n x 1) vector of stationary endogenous variables at time t, A is again a (n x n) matrix representing the structural contemporaneous relationships between the endogenous variables, and B is a (n x n) matrix (often a diagonal matrix containing the errors' standard deviations). I further assume that both A and B are non-singular. $\bar{c} = \mathrm{A}c$ is a (n x 1) vector of constant terms, $\bar{\Phi}_1 = \mathrm{A}\Phi_1$, …, $\bar{\Phi}_p = \mathrm{A}\Phi_p$ are coefficient matrices of the p lagged values of all endogenous variables, and U_t is a (n x 1) vector containing the structural shocks with $E(U_t) = 0$ and variance-covariance matrix $E(U_t U_t') = \sum_U = \mathrm{I}_n$.

A SVAR model can be used to identify shocks and trace these out by employing impulse response analysis and forecast error variance decomposition through imposing restrictions on the matrices A and B. Incidentally, because a SVAR model is a structural model, it departs from a reduced form VAR(p) model and only restrictions for A and B can be added.

3.2 The TVAR model

A challenge for the benchmark VAR model is that it might not be able to capture possible non-linearities in the transmission of financial stress in the economic activity. Uncovering non-linearities in the data allows us to account for the potential shifts in the behaviour of economic variables depending on different financial stress regimes. For this reason, besides the benchmark VAR model, I define a threshold vector autoregressive (TVAR) model, which is one of the most extensively used class of models in the nonlinear time series literature and particularly in fiscal policy analysis. The TVAR model has a number of interesting features that make it attractive for this purpose.

First, by splitting the time series endogenously into different regimes, the TVAR is a relatively simple way to capture possible nonlinearities such as asymmetric reactions to shocks of various macroeconomic variables in the low and high financial stress regimes. Within each regime the time series is assumed to be described by a linear model. Because the effects of the shocks are allowed to depend on the size and the sign of the shock, and also on the initial conditions, the impulse response functions are no longer linear, and it is possible to distinguish, for instance, between the effects of various macroeconomic variables under different financial stress regimes.

Second, another advantage of the TVAR methodology is that the variable, by which different regimes are defined (s_t), can be an endogenous variable included in the VAR. Therefore, this makes it possible that regime switches may occur after the shock to each variable. In particular, the fiscal policy shock might either boost the output or increase the financial stress conditions that harm the prospects of economic growth, and the overall effect GDP of a fiscal expansion might become negative.

I follow the approach used by Afonso et al., (2011), Balke (2000) and Atanasova (2003) for the identification and estimation of a structural TVAR model containing 5 stationary endogenous variables, namely GDP growth (y), inflation (π), the fiscal variable (f), the short-term interest rate (i), and the indicator for financial market conditions (s), for which I have chosen the Country-Level Index of Financial Stress (CLIFS), developed by Duprey et al. (2015) for the ECB. Based on its linear version of equation (2), the TVAR model can be specified through the structural A-B form as[2]:

$$\mathrm{A}Y_t = \begin{cases} \bar{\Phi}^L(L)Y_{t-1} + BU_t & if\ I[s_{t-d}, \gamma] = 0 \\ (\bar{\Phi}^L(L) + \bar{\Phi}^H(L))Y_{t-1} + BU_t & if\ I[s_{t-d}, \gamma] = 1 \end{cases} \tag{3}$$

where $\mathrm{A} = (\mathrm{I} - \bar{\Gamma}^L)$ when $I[.] = 0$ and $\mathrm{A} = (\mathrm{I} - \bar{\Gamma}^L - \bar{\Gamma}^H)$ when $I[.] = 1$. Assuming $B = \mathrm{I}$, the model can therefore be rewritten as:

$$Y_t = \begin{cases} \bar{\Gamma}^L Y_t + \bar{\Phi}^L(L)Y_{t-1} + U_t & if\ I[s_{t-d}, \gamma] = 0 \\ (\bar{\Gamma}^L + \bar{\Gamma}^H)Y_t + (\bar{\Phi}^L(L) + \bar{\Phi}^H(L))Y_{t-1} + U_t & if\ I[s_{t-d}, \gamma] = 1 \end{cases} \tag{4}$$

or in the compact form:

$$Y_t = \bar{\Gamma}^L Y_t + \bar{\Phi}^L(L)Y_{t-1} + \left(\bar{\Gamma}^H Y_t + \bar{\Phi}^H(L)Y_{t-1}\right)I[s_{t-d}, \gamma] + U_t \tag{5}$$

where Y_t is a (n x 1) vector of stationary endogenous variables; $\bar{\Gamma}^L$ and $\bar{\Gamma}^H$ are (n x n) matrices representing the structural contemporaneous relationships between the endogenous variables in the low-stress and high-stress regime respectively. I assume that $\bar{\Gamma}^L$ and $\bar{\Gamma}^H$ have a recursive structure. $\bar{\Phi}^L(L) = \mathrm{A}\sum_{i=1}^{p} \Phi_i^L L^{i-1}$ and $\bar{\Phi}^H(L) = \mathrm{A}\sum_{i=1}^{p} \Phi_i^H L^{i-1}$ are (structural) lag polynomial matrices in the low-stress and high-stress regime respectively; U_t is again a (n x 1) vector of structural shocks, which are assumed to be white noise, uncorrelated and homoscedastic, with variance–covariance matrix typically normalized such that: $E(U_t) = 0$ and $E(U_t U_t') \equiv \sum_U = \mathrm{I}_n$. This means, first, that there are as many structural shocks as variables in the model. Second, structural shocks by

[2] Constants or other deterministic regressors have been suppressed for notational convenience.

definition are mutually uncorrelated, which implies that $\sum_U$ is diagonal. Third, I normalize the variance of all structural shocks to unity. The latter normalization does not involve a loss of generality, as long as the diagonal elements of the matrix A remain unrestricted. s_{t-d} is the threshold variable that determines the dynamics of Y_t in different regimes, with a possible lag d; γ is the threshold value at which the regime switching occurs; $I[.]$ is an indicator function that governs the regime switches and that takes the value of 1 if, the threshold variable s_{t-d} is higher than the threshold value γ (high-stress regime), and 0 otherwise (low-stress regime).

3.3 Testing nonlinearity

Before starting with the estimation of a linear vs. a non-linear VAR model, I need to test if the system is indeed non-linear. First, I determine the threshold value over all possible values of the threshold variable, and second, I run a nonlinearity test for a threshold VAR model against a linear VAR model to see whether the threshold value is statistically significant. To do so, I follow the procedure introduced by Hansen (1996). The threshold is thus determined endogenously by a grid search over all possible values of the threshold variable, where the grid Θ covers the sample range of the threshold variable and is trimmed at a lower and upper bound Θ = $[\underline{\gamma}, \overline{\gamma}]$ in order to ensure a sufficient number of data points for the estimation in both regimes. To avoid over-fitting, the possible values were set so that at least 15% of the observations plus the number of coefficients is included in each regime. From the grid, the estimated threshold value corresponds to the model with the smallest determinant of the variance-covariance matrix of the estimated residuals $\sum_\varepsilon$ (which is the multivariate equivalent to a sum of squared residuals criterion in a univariate model):

$$\hat{\gamma} = \underset{\gamma \epsilon \Theta_n}{\operatorname{argmin}} \log |\textstyle\sum_\varepsilon(\gamma)| \tag{6}$$

Now I can test whether the chosen threshold for each country is statistically significant by employing non-linearity tests for each equation of the VAR system. The null hypothesis that the coefficients of $\bar{\Gamma}^H$ and $\bar{\Phi}^H(L)$ equal zero can be implemented by a Wald test. However, standard inference cannot be applied as the unknown threshold γ is not identified under the null hypothesis of no threshold (Hansen, 1996). Therefore, I construct three test statistics to be able to evaluate the statistical relevance of the endogenously chosen thresholds: sup-Wald, which is the maximum value of the Wald statistics over all possible γ; the avg-Wald being an average of Wald statistics; and exp-Wald, which is the sum of exponential Wald statistics. The latter two statistics are suggested by Andrews and Ploberger (1994). The distribution of these statistics does not follow a chi-square distribution since γ is not identified. Therefore, to conduct inference, the bootstrap procedure of Hansen (1996, 1997) is used to simulate an empirical distribution for the sup-Wald, avg-Wald and exp-Wald statistics with p-values obtained from 500 replications of the simulation procedure.

3.4 Estimation technique

In order to allow estimation of the structural TVAR model of equation (5), we first need to derive its reduced-form representation because consistent estimation of the coefficients of the structural VAR model is not feasible. This involves expressing Y_t as a function of lagged Y_t only. To derive the reduced-form representation, I pre-multiply both sides of equation (5) by A^{-1}. Hence, the reduced-form TVAR is described as:

$$Y_t = c^L + \Phi^L(L)Y_{t-1} + (c^H + \Phi^H(L)Y_{t-1})I[s_{t-d}, \gamma] + \varepsilon_t \tag{7}$$

where again Y_t denotes the (n x 1) vector of the stationary endogenous variables, $c^L = \mathrm{A}^{-1}\bar{c}^L$ and $c^H = \mathrm{A}^{-1}\bar{c}^H$ are (n x 1) vectors of intercept terms in the low-stress and high-stress regime respectively, $\Phi^L(L) = \mathrm{A}^{-1}\overline{\Phi}^L(L)$ and $\Phi^H(L) = \mathrm{A}^{-1}\overline{\Phi}^H(L)$ are the (reduced-form) lag polynomial matrices in the low-stress and high-stress regime respectively, and $\varepsilon_t = \mathrm{A}^{-1}BU_t$ is the vector of reduced-form error terms. The reduced-form disturbances are then linear combinations of the structural form errors.

If the hypothesis of linearity (i.e. H_0: $\bar{\Gamma}^H = \overline{\Phi}^H(L) = 0$) is rejected by the data, I can proceed with the estimation of the Threshold VAR. Given the linearity of the model within each regime, the parameters can be recovered by least squares (LS). By definition the OLS estimators ($\widehat{\Phi}$, $\widehat{\sum_\varepsilon}$, $\hat{\gamma}$) minimize jointly the sum of the squared errors SSE_n. The computationally easiest method to obtain the OLS estimates is through concentration. Conditional on γ, SSE_n is linear in Φ and $\sum_\varepsilon$. The estimation yields the conditional estimators $\widehat{\sum_\varepsilon}$ and $\widehat{\Phi}$. However, once estimated, the state dependent dynamics of TVARs allows for non-linear and asymmetric impulse-response functions. Note that the TVAR model is linear within each regime, but the changes in the parameters across regimes account for non-linearities.

3.5 Identification

From the reduced-form representation of the TVAR model of equation (7), it is clear by inspection that the reduced-form innovations ε_t are in general a weighted average of the structural shocks U_t, where the coefficients of the A and B matrix represent the weights attached to the structural shocks. As a result, studying the response of the vector Y_t to reduced-form shocks ε_t will not tell us anything about the response of Y_t to the structural shocks U_t. It is the latter responses that are of interest if one wants to learn about the structure of the economy. These structural responses depend on $\overline{\Phi}^L(L)$ and $\overline{\Phi}^H(L)$. Now I have to recover the elements of A^{-1} and B from consistent estimates of the reduced-form parameters, because knowledge of A^{-1} and B would enable us to reconstruct U_t from $BU_t = \mathrm{A}\varepsilon_t$, $\overline{\Phi}^L(L)$ from $\overline{\Phi}^L(L) = \mathrm{A}\Phi^L(L)$, and $\overline{\Phi}^H(L)$ from $\overline{\Phi}^H(L) = \mathrm{A}\Phi^H(L)$. From the equality $\varepsilon_t = \mathrm{A}^{-1}BU_t$, and knowing that from the normalization of the covariance matrix of the structural shocks we have $E(U_tU_t') \equiv \sum_U = \mathrm{I}_n$, the covariance matrix of the reduced-form disturbances simplifies to:

$$E(\varepsilon_t\varepsilon_t') \equiv \textstyle\sum_\varepsilon = E((\mathrm{A}^{-1}BU_t)(\mathrm{A}^{-1}BU_t)') = \mathrm{A}^{-1}B\sum_U B'\mathrm{A}^{-1\prime} = \mathrm{A}^{-1}BB'\mathrm{A}^{-1\prime} \tag{8}$$

where I made use of $\sum_U = \mathrm{I}_n$. $\sum_\varepsilon$ is consistently estimated by OLS as described in subsection 3.1.2. After estimating $\sum_\varepsilon$, the objective is to recover the matrix A^{-1} and B. However, to identify all the elements of the matrix A^{-1} and B is not feasible, because the covariance matrix of the reduced-form shocks is symmetric. For this reason, additional restrictions are needed. Each matrix A and B has n^2 unknown parameters to estimate and the distinct estimated values from $\sum_\varepsilon$ are $n(n+1)/2$. Therefore, I need to impose $2n^2 - n(n+1)/2 = n^2 + n(n-1)/2$ restrictions on A and B parameters to exactly identify the system. This order condition for identification is easily checked in practice but it is a necessary condition for identification only. A rank condition should also be checked to rule out possible colinear (i.e. redundant) restrictions. In particular, the rank condition may fail, depending on the numerical values of the elements of A^{-1}. In this regard, following Rubio- Ramirez, Waggoner and Zha (2010), one can easily check that the rank condition in structural VAR models is satisfied for both local and global identification.

For the purpose of this work, I use a recursive identification scheme, namely I rely on a Cholesky decomposition of the variance-covariance matrix of residuals $\sum_\varepsilon$ in each regime to recover the elements of A^{-1} and B. A possible solution for these elements is found solving the following equation:

$$\sum_{\varepsilon} = PP' \tag{9}$$

where the matrix $P = \mathrm{A}^{-1}B$ is known as the Cholesky decomposition of $\sum_{\varepsilon}$. Once the elements of A^{-1} and B have recovered, the impact of the different structural shocks can be evaluated. The recursive identification scheme implies that the matrix A^{-1} has a lower-triangular form, whereas the matrix B is diagonal. These particular forms of A^{-1} and B satisfy the required number of restrictions, thereby it will be possible to estimate the structural shocks U_t from the reduced form VAR residuals ε_t.

Instead of deducing causal relationships from the data itself, the recursive identification scheme implies a certain causal ordering on the matrix Y_t, so that the disturbance to the first variable is predetermined relative to the disturbances to the variables following in the order. For this reason, the recursive structure embodied in A^{-1} and B needs economic justification, because the order of equations variables matters. In our model, the five variables are thus order as follows: GDP growth (y), inflation (π), the fiscal variable (f), the short-term interest rate (i), and the Country-Level Index of Financial Stress (s). Specifically, the recursive identification procedure implies that disturbances to GDP growth have an immediate impact on all the other variables; the disturbances to inflation have an immediate impact on all variables except on GDP growth; the disturbances to the fiscal variable have an immediate impact on the short-term interest rate and the financial stress indicator but do not have a contemporaneous impact on GDP growth and inflation, and so on. A similar causal ordering was also used in Bernanke et al. (1997) and in Leeper et al. (1996) in which endogenous variables are ordered as follows: output, prices, monetary policy variables and financial market variables. As a result, the relation between the reduced and the structural error terms is then given by:

$$\varepsilon_t = \mathrm{A}^{-1}BU_t \tag{10}$$

$$\begin{pmatrix} \varepsilon_t^{y} \\ \varepsilon_t^{\pi} \\ \varepsilon_t^{\mathrm{f}} \\ \varepsilon_t^{\mathrm{i}} \\ \varepsilon_t^{\mathrm{s}} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ -a_{21} & 1 & 0 & 0 & 0 \\ -a_{31} & -a_{32} & 1 & 0 & 0 \\ -a_{41} & -a_{42} & -a_{43} & 1 & 0 \\ -a_{51} & -a_{52} & -a_{53} & -a_{54} & 1 \end{pmatrix} \begin{pmatrix} b_{11} & 0 & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 & 0 \\ 0 & 0 & b_{33} & 0 & 0 \\ 0 & 0 & 0 & b_{44} & 0 \\ 0 & 0 & 0 & 0 & b_{55} \end{pmatrix} \begin{pmatrix} U_t^{\mathrm{y}} \\ U_t^{\pi} \\ U_t^{\mathrm{f}} \\ U_t^{\mathrm{i}} \\ U_t^{\mathrm{s}} \end{pmatrix}$$

I order the $CLIFS$ last which implies that the $CLIFS$ reacts contemporaneously to all variables in the system. I assume that all new changes in both macroeconomic aggregates and economic policy that occur during one quarter are transmitted to financial markets within this quarter. The ordering of the fiscal variable after output is motivated by the need to identify the effects of automatic stabilizers in the economy. Hence, following Blanchard and Perotti (2002), I assume that all reactions of fiscal policy within each quarter (e.g. changes in government debt) are purely automatic because of implementation lags of fiscal policy measures. The interest rate shows up after the fiscal variable since the short-term interest rate can react contemporaneously to fiscal policy, but not vice versa. Moreover, the short-term interest rate does not have a contemporaneous impact on output growth or the inflation rate but can have an immediate impact on the $CLIFS$.

3.6 Linear impulse response functions

In VAR models, the interaction between economic variables is studied by considering the effects of changes in one variable on the other variables of interest. This kind of analysis is known as impulse response analysis. Impulse responses trace out the response of current and future values of each of the variables to a one-unit increase in the current value of one of the VAR errors, assuming that this error returns to zero in subsequent periods and that all other errors are equal to zero. For linear VAR models the impulse response functions are indeed linear and of less complexity than nonlinear IRFs.

In the reduced-form VAR model (1), a nonzero component of ε_t corresponds to an equivalent change in the associated left-hand side variable which in turn will induce further changes in the other variables of the system in the next periods. The marginal effect of a single nonzero element in ε_t can be studied conveniently by representing the VAR model (1) in the compact form[3]:

$$\Phi(L)Y_t = \varepsilon_t \tag{11}$$

where $\Phi(L) = \mathrm{I}_n - \sum_{i=1}^{p} \Phi_i L^i$ denotes polynomials in the lag operator L of the endogenous variables. Assuming stationarity, we then invert the VAR in compact form (11) and consider the corresponding vector moving average (VMA) representation.

$$Y_t = \Phi(L)^{-1}\varepsilon_t = C(L)\varepsilon_t \tag{12}$$

where $C(L) = \sum_{l=0}^{\infty} C_l L^l = \Phi(L)^{-1}$. The marginal response of $Y_{i,t+l}$ to a unit impulse ε_{jt} is given by the (i,j)-th elements of the matrices C_l, viewed as a function of l. Hence, the elements of C_l represent the responses to ε_t innovations. The VMA representation of the reduced-form VAR

[3] We ignore deterministic terms to simplify notation and because they are not useful for impulse response analysis.

model is useful to trace out the dynamic path of the various shocks on the variables included in the system as the variables are expressed as a function of current and past innovations ε_t. Because the ε_t are just the 1-step forecast errors, these impulse responses are sometimes called forecast error impulse responses and the corresponding MA representation is called Wold representation.

Because in standard VARs the residual covariance matrix $\sum_\varepsilon$ is generally not diagonal, the components of ε_t may be contemporaneously correlated. Consequently, the ε_{lt} shocks are not likely to occur in isolation in practice. Therefore, tracing such shocks may not reflect what actually happens in the system if a shock hits. In other words, forecast error shocks may not be the right ones to consider if one is interested in understanding the interactions within the system under consideration. Therefore, we consider the structural benchmark VAR model of equation (2). The SVAR model in the compact form is:

$$\overline{\Phi}(L)Y_t = BU_t \tag{13}$$

where $\overline{\Phi}(L) = \mathrm{A} - \sum_{l=1}^{p} \overline{\Phi}_l \, L^l$ denotes polynomials in the lag operator L of the endogenous variables. Then, we invert the SVAR in compact form (13) and consider the corresponding structural vector moving average (SVMA) representation:

$$Y_t = \overline{\Phi}(L)^{-1}BU_t = \sum_{l=1}^{\infty} C_i \, A^{-1}BU_{t-l} = \sum_{l=1}^{\infty} D_l \, U_{t-l} \tag{14}$$

where the $D_l = C_l \mathrm{A}^{-1}B$ contain the structural impulse responses, and U_t are obtained imposing the structural identification scheme (see subsection 3.5). In this case, the marginal response of $Y_{i,t+l}$ to a unit impulse U_{jt} is given by the (i,j)-th elements of the matrices D_l, viewed as a function of l. Hence, the elements of D_l represent the responses to U_t. Now, the estimation of impulse responses is straightforward by substituting estimated structural form parameters in the formulas for computing them. In other words, the linear structural impulse response functions can be defined as the change in the conditional expectation of the vector Y_{t+l} as a result of the shock U_{jt}:

$$IRF_y\left(l, \delta_{jt}\right) = E\left(Y_{t+l} \middle| U_{jt} = \delta_{jt}\right) - E\left(Y_{t+l} \middle| U_{jt}^0 = \delta_{jt}^0\right) \tag{15}$$

where Y_{t+l} is a vector of variables at horizon l, $U_{jt} = \delta_{jt}$ denotes the shock to the j-th equation that the expectations are conditioned on, and $U_{jt}^{0} = \delta_{jt}^{0}$ denotes stochastic disturbance to the j-th equation at time 0 that would occur under the no shock scenario.

3.7 Generalized impulse response functions

In non-linear VAR models, the computation of impulse responses is considerably more complicated than in linear VARs. As seen in subsection 3.6, in the linear case, the impulse responses can be derived directly from the estimated coefficients and the estimated responses are symmetric both in terms of the sign and of the size of the structural shocks. Furthermore, these impulse responses are constant over time as the covariance structure does not change. For this reason, linear VARs are said to be history-independent because no shocks hit the economy in intermediate periods. This can be justified by their Wold representation of equation (14).

However, these convenient properties do not hold within the class of nonlinear models as shown by Potter (1994) and Koop et al. (1996). In nonlinear models, the moving average representation is nonlinear in the structural disturbances U_t, because some shocks may lead to switches between regimes, and thus their Wold representation does not exist. This implies that, in contrast to linear models, we cannot construct the impulse responses as the paths the variables follow after an initial shock, assuming that no other shock hits the system. To cope with these issues, the analysis requires the computation of generalized impulse response functions (GIRFs), as developed by Koop et al. (1996), defined as the difference between the forecasted paths of variables with and without a shock to a variable of interest. The advantage of GIRFs is that not only it allows for the analysis of regime-dependent responses, but also that effects of shocks of different sizes and directions can be analyzed. Due to this history- and shock-dependence, GIRFs lend themselves as an appropriate framework to analyze the above-mentioned dimensions of non-linearity such as regime-dependencies, asymmetries (positive vs. negative shocks) and shock non-linearity (small vs. large shocks).

The generalized impulse response functions (GIRFs) are computed following Koop, Pesaran and Potter (1996), and they are designed to trace out the effects of orthogonal structural shocks as in Kilian and Vigfusson (2011). Formally, the GIRFs are defined as:

$$GIRF_y\left(l, \delta_{jt}, \Omega_{t-1}\right) = E\left(Y_{t+l} \middle| U_{jt} = \delta_{jt}, \Omega_{t-1}\right) - E\left(Y_{t+l} \middle| U_{jt}^{0} = \delta_{jt}^{0}, \Omega_{t-1}\right) \tag{16}$$

where again Y_{t+l} is a vector of variables at horizon l, Ω_{t-1} is the information set available before the time of shock U_{jt}. $U_{jt} = \delta_{jt}$ denotes the shock to the j-th equation that the expectations are conditioned on, and $U_{jt}^0 = \delta_{jt}^0$ denotes stochastic disturbance at time 0 that would occur under the no shock scenario. This implies that there is no restriction regarding the symmetry of the shocks in terms of their sizes because the effects of a U_{jt} shock depend on the magnitude of the current and subsequent shocks. Moreover, in the high-stress regime, the size of the fiscal shock matters, since a small shock is less likely to induce a change in the regime. Likewise, the impulse responses depend also on the entire history of the variables that affect the persistence of the different regimes.

The impulse responses have to be simulated for various sizes and for the signs of the shocks. The algorithm proceeds as follows[4] (a detailed description of the simulation method and the way the GIRFs are computed is provided in Appendix II): First, the shocks for the periods from 0 to q are drawn from the residuals of the estimated TVAR model. Then, for each initial value of the variables that is, for each point of our sample, this sequence of shocks is fed through the model to produce forecasts conditional on initial conditions. The result is a forecast of the variables conditional on initial values and a particular sequence of shocks. These steps are repeated for the same initial condition and the same set of residuals except for the shock to the variable of interest, which is set to +/-1 standard error and +/-2 standard errors at t = 0. Second, I calculate the forecasts conditional on the shocks and on the initial conditions with and without an additional shock at t = 0, and the difference between these two is the impulse response function. This procedure is replicated 500-times for each initial condition and the median, average and quantiles are saved. Then I compute averages over the initial conditions from each regime to get the impulse responses for both regimes.

[4] I used the WinRATS code provided by Nathan Balke, which I modified for the purpose of this work.

3.8 Forecast error variance decompositions

The forecast error decomposition is a part of structural analysis which "decomposes" the variance of the forecast error into the contributions from specific shocks at a given horizon. The FEVD thus indicates which shocks contribute towards the fluctuations of each variable in the system. Because of that, FEVD is generally used in dynamic analysis to (1) to demonstrate how important a shock is in explaining the variations of the variables in the model, and (2) to show how that importance changes over time.

The computation and analysis of forecast error variance decomposition (FEVD) in linear models assumes that impulse responses and variance decomposition are not state dependent nor shock and composition dependent as it happens in the non-linear models. Based on the definition of linear impulse response function of equation (15), the corresponding FEVD for horizon h equals:

$$FEVD_{ij}(h) = \frac{\sum_{l=0}^{h} IRF_y\left(l, \delta_{jt}\right)^2}{\sum_{j=1}^{k} \sum_{l=0}^{h} IRF_y\left(l, \delta_{jt}\right)^2} = \frac{\sum_{l=0}^{h} IRF_y\left(l, \delta_{jt}\right)^2}{\sigma_i(h)} \quad i, j = 1, \dots, k \qquad (17)$$

where j and i refer to the j-th shock and i-th variable in Y_t respectively, $IRF_y\left(l, \delta_{jt}\right)$ are the linear impulse response functions computed in subsection 3.6 and h is the horizon. $\sum_{j=1}^{k} FEVD_{ij}(h) = 1$ for a given $i, l = 1, \dots, h$ and $\sigma_i(h)$ denotes the h-step forecast error variance of the i-th variable. Therefore, in linear VARs, $FEVD_{ij}(h)$ measures the relative contribution of a shock to the j-th equation in relation to the total impact of all k shocks on the i-th variable in Y_t after h periods, and these contributions sum to unity.

3.9 Generalized forecast error variance decompositions

To allow for the analysis of regime-dependency of variance decompositions, I follow the approach of Lanne and Nyberg (2016), who propose a generalized version of the forecast error variance decomposition for multivariate nonlinear models. Several authors have also used Lanne and Nyberg's GFEVD method in their research (Mumtaz and Theodoridis, 2019, Caggiano, Castelnuovo and Figueres, 2020, Caggiano, Castelnuovo and Pellegrino, 2017). In particular, Mumtaz and Theodoridis (2019) use this method to study the relative contribution of the monetary policy shock and other shocks to the volatilities of economic variables, such as employment, inflation and term spreads. Caggiano et al. (2020) conduct GFEVD to analyze asymmetric spillover effects of US economic policy uncertainty shocks on the Canadian unemployment rate. Caggiano et al. (2017) construct GFEVD to show that uncertainty shocks are relatively more important when the economy is at the zero lower bound.

The computation of the state-dependent Generalized Forecast Error Variance Decomposition (GFEVD) for our TVAR model is similar to the one proposed in Lanne and Nyberg (2016). The innovations are: i) it is designed to simulate the importance of an orthogonal structural shock, and ii) it considers a one standard deviation shock in each variable. In particular, conditional on a specific history Ω_{t-1} and a forecast horizon of interest h, the $GFEVD_{ij}$ that refers to a variable i and a shock j whose size is δ_{jt} is given by:

$$GFEVD_{ij}(h, \Omega_{t-1}) = \frac{\sum_{l=1}^{h} GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)^2}{\sum_{j=1}^{k} \sum_{l=1}^{h} GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)^2} \quad i, j = 1, \dots, k \tag{18}$$

where h is an indicator that keeps track of the forecast errors, and k denotes the number of shocks to the i-th variable in the vector Y_t. Ω_{t-1} is the information set available before the time of shock δ_{jt}. Differently from Lanne and Nyberg (2016), in our case the object $GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)$ are the generalized impulse response functions à la Koop, Pesaran, and Potter (1996) computed in subsection 3.7 by considering an orthogonal shock as in Kilian and Vigfusson (2011)[5]. In our application we are interested in the contribution of an identified fiscal shock to the GFEVD of output growth and financial stress variable.

[5] The object $GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)$ in Lanne and Nyberg's (2016) expression, refers to the GIRFs à la Pesaran and Shin (1998). This definition of the GIRF refers to a non-orthogonalized shock and it can be applied both to linear and nonlinear VAR models. Details can be found in Pesaran and Shin (1998) and Lanne and Nyberg (2016).

In the above equation, the denominator measures the aggregate cumulative effect of all the shocks, while the numerator is the cumulative effect of the j-th shock. By construction, $GFEVD_{ij}(h, \Omega_{t-1})$ lies between 0 and 1 and for non-linear VARs it measures the relative contribution of a shock to the j-th equation in relation to the total impact of all k shocks on the i-th variable in Y_t after h periods, and these contributions sum to unity.

This formula is similar to the traditional forecast error variance decomposition for a linear VAR model with orthogonal shocks. The difference is that this formula uses generalized impulse responses instead of traditional impulse responses. In a nonlinear model, the GIRFs and hence the GFEVDs, cannot typically be expressed in closed form, but the effects of a shock δ_{jt} typically depend on its size and sign as well as the history, and for this reason, as the case of GIRFs, the computation of GFEVDs requires simulation methods. Specifically, the GFEVDs can be obtained as the average of $GFEVD_{ij}(h, \Omega_{t-1})$ over shocks obtained by bootstrapping from the residuals of the estimated model, and over all the histories in the same way as shown for the GIRFs by Koop et al. (1996). This should yield the GFEVD characteristic of the data at hand, and it naturally solves the problem of setting the size of shocks to each equation in a multivariate model (a detailed description of the simulation method and the way the GFEVDs are computed is provided in Appendix III).

Chapter 4

Variables and data

4.1) Data and preliminary analysis – 4.2) Output growth – 4.3) Inflation - 4.4) The fiscal variable – 4.5) Fiscal developments' overview – 4.6) Short-term interest rate - 4.7) The Country-Level Index of Financial Stress

4.1 Data and preliminary analysis

The TVAR model is estimated using quarterly data for the UK, Germany, Italy and France for the period 1997:1-2021:1. The TVAR of equation (4) consists of a five-dimensional system of endogenous variables $Y_t = \{y_t, \pi_t, f_t, i_t, s_t\}$, namely GDP growth ($y$), inflation ($\pi$), the fiscal variable ($f$), the short-term interest rate (i), and the Country-level index of financial stress (s). Each variable is explained in detail in the following subsections. Further details about the data description and sources are provided in Appendix I.

Before estimating the model, I perform a battery of tests to check for the adequacy of the model. First, I check for the stability of our model by computing the roots of the characteristic polynomial, i.e. I employ the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test. For all five variables, both tests include a constant but no trend. Although some variables exhibit evidence of nonstationary behavior (cfr. Table 4 in appendix IV) and the Trace and Maximum Eigenvalue tests find evidence of cointegration (cfr. Table 5 in appendix IV), the model is specified without imposing cointegrating relationships. This choice is dictated by the fact that there is uncertainty about the number of cointegrating relationships as Table 5 shows that the order of integration changes when the tests are performed on a VAR including the integrated variables only rather than the entire set of variables. Hence, I avoid possible misspecification errors due to imposing long-run relationships not supported by theoretical underpinnings. There is an issue of whether the variables in a VAR need to be stationary. Sims (1980) and Sims, Stock, and Watson (1990) argued that the goal of a VAR analysis is to determine the interrelationships among the variables, not to determine the parameter estimates. Similarly, it is argued that the data need not be detrended. In a VAR, a trending variable will be well approximated by a unit root plus drift. However, the majority view is that the form of the variables in the VAR should mimic the true data-generating process. This is particularly true if the aim is to estimate a structural model as in our case.

I determine the optimal lag length (p) by minimizing the Schwarz information criterion, which attaches a larger penalty to the number of coefficients estimated in the model, hence I use only one lag given the low number of observations in the high stress regime (cfr. Table 6 in appendix IV). The main reason is that within the high financial stress regimes the number of observations is too low to allow estimating a TVAR model with five variables and the conventionally used four lags. The optimal value of the time delay (d) is chosen in such a way that it provides the minimum residuals variance. Therefore, the time delay of the threshold variable is set to 1.

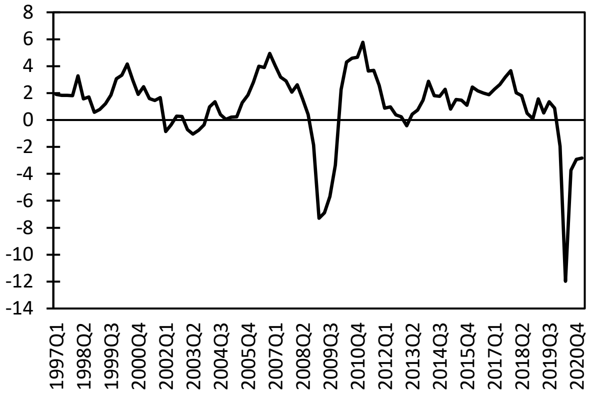
4.2 Output growth

Figure 1 exhibits the developments of real GDP growth in Germany, Italy, the U.K. and France in the period 1997:1-2021:1, based on the data provided by the International Financial Statistics (IFS) database of the International Monetary Fund (IMF). Output growth is the first variable in our model, and it is computed taking the y-o-y difference of the logarithm of real GDP.

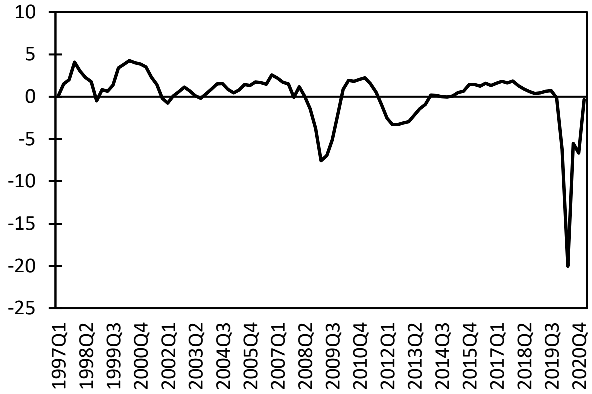
In the countries under analysis, real GDP growth did not fluctuate substantially over the period of consideration, except in Germany, where GDP growth experienced large swings especially during recession periods. All countries report a substantial decrease in economic activity following the global financial crisis, but it then they recovered to near pre crisis levels within approximately two years. However, growth rates declined again due to the European sovereign debt crisis of late 2009. After that, economic growth strengthened further up to 2018 for all countries, with some exceptions for the U.K., where growth experienced a slow decrease since 2014. In 2020, economic activity fell sharply due to the Covid-19 pandemic and the measures taken to contain it. The fallout from the pandemic was already apparent in the first quarter, but the brunt of the impact fell in the second quarter when GDP contracted by approximately 20% in Italy, the U.K. and France, and by 12% in Germany. In the third quarter, GDP rebounded quickly in all countries, as a relaxation of confinement measures and the revival of foreign trade led to a partial resumption of activity in both industry and services. In the first quarter of 2021 GDP recovered to its pre-crisis levels in Italy and France, but it remained negative in the U.K. and Germany.

Figure 1: Output growth

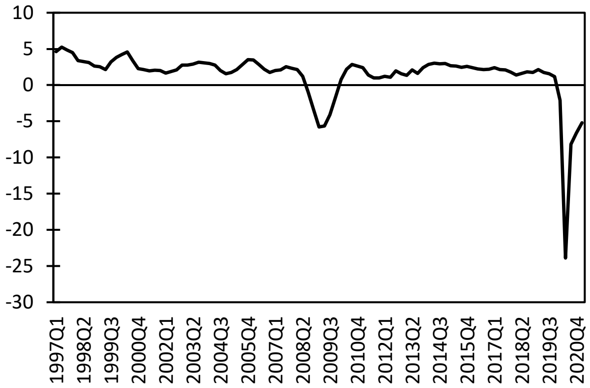
1.1 Germany



1.2 Italy



1.3 U.K.



1.4 France

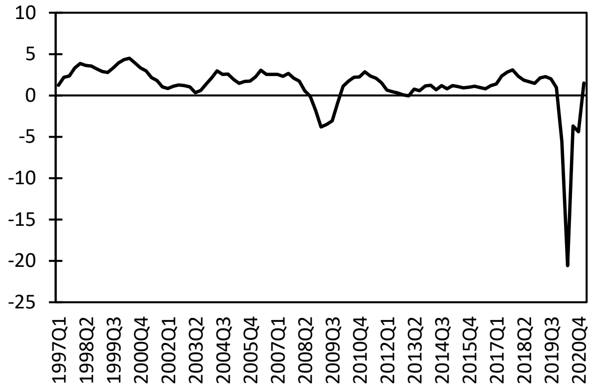


Fig. 1: Real GDP growth of Germany, Italy, U.K. and France. Y-axis displays the values of the growth rate. X-axis displays the time span, which is 1997:1-2021:1. Source: International Monetary Fund (IMF).

4.3 Inflation

Figure 2 exhibits the developments of the inflation rate in Germany, Italy, the U.K. and France in the period 1997:1-2021:1, based on the data provided by the International Financial Statistics (IFS) database of the International Monetary Fund (IMF). The inflation rate is the second variable in our model, and it is computed taking the y-o-y difference of the logarithm of GDP implicit deflator.

Figure 2: Inflation

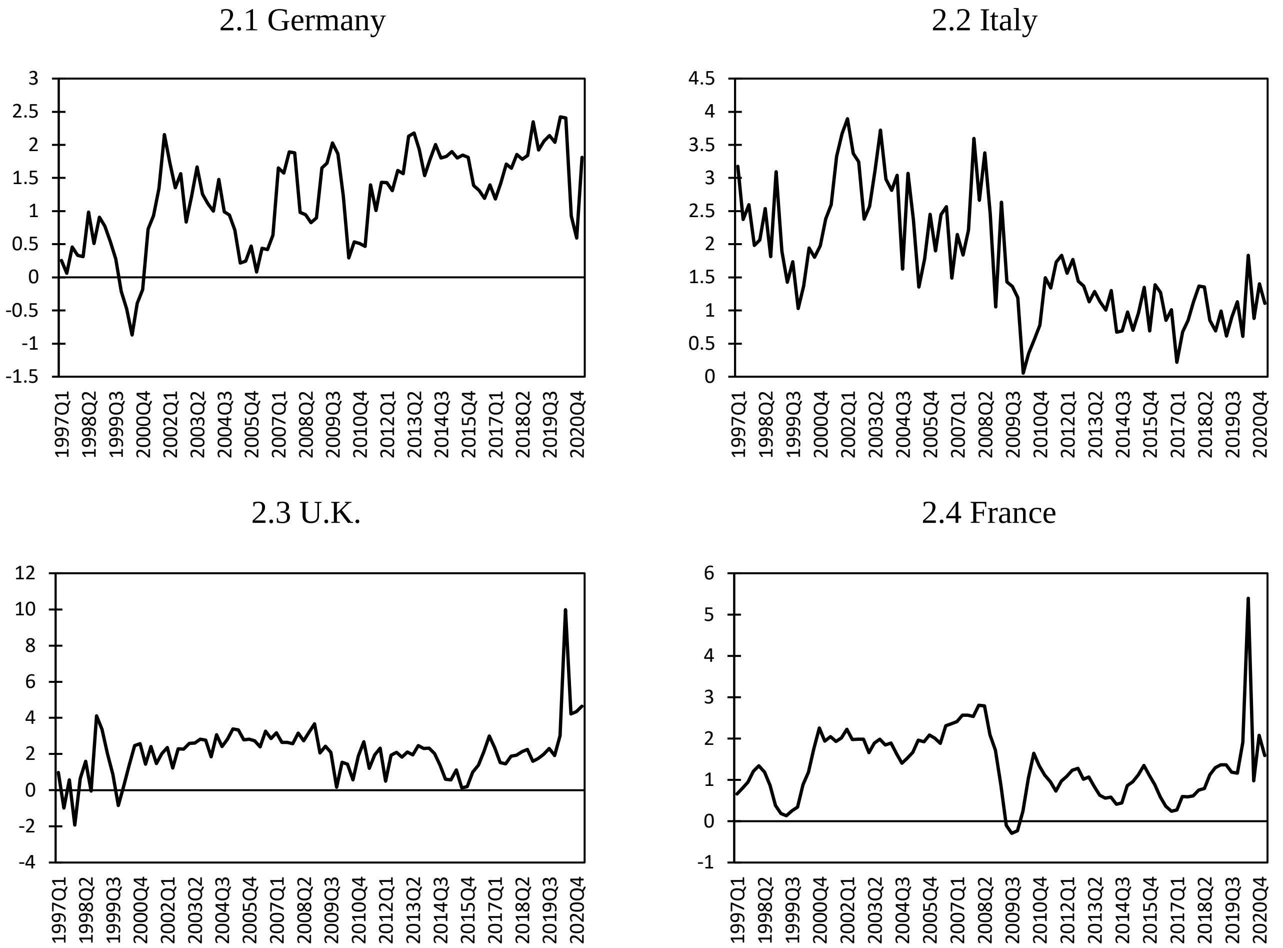


Fig. 2: Inflation rate of Germany, Italy, U.K. and France. Y-axis displays the values of the inflation rate. X-axis displays the time span, which is 1997:1-2021:1. Source: International Monetary Fund (IMF).

From figure 2 we can identify periods of dramatically falling inflation rates in the aftermath of the global financial crisis for all countries under consideration, especially in Italy and France. Moreover, in the second quarter of 2020 during the Covid-19 pandemic, inflation surged in the U.K. and France peaking at 10% and 5.5% respectively immediately prior to news of the situation breaking. On the other hand, Italy exhibits inflation levels that are substantially lower, whilst Germany reports decreasing rates approaching to 2.4% within the same quarter. This decline was due to a sharp contraction in economic activity, which significantly weakened consumer demand, but specifically for Germany it resulted from the impact of the temporary reduction in the VAT rate.

4.4 The fiscal variable

A relevant issue with VARs used for fiscal policy analysis is the choice of the variables that describe fiscal developments. For example, a discretionary increase in government revenues may have a different macroeconomic impact depending on which taxes are increased (labor versus consumption taxes), depending on whether a tax rate or the tax bases are modified, etc. At the same time, if one is data restricted, it is not possible to build VAR models with an excessive number of endogenous variables to describe fiscal policy.

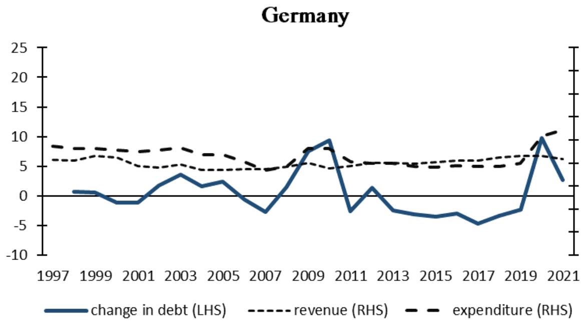
I preferred to work with a parsimonious VAR structure to describe fiscal policy in the most aggregated form. Therefore, I used the government debt-to-GDP ratio because it reflects the developments both in government revenue and expenditure. Moreover, the government debt ratio captures also government actions that may not be fully reflected in the fiscal balance (e.g. purchase of financial assets, recapitalization of banking sector, the calling of previously issued government guarantees or any stock-flow adjustments) and has thus, in principle, a wider coverage of government actions than the fiscal balance. In addition, usually government debt is not a policy variable, with governments focusing more in the short run on the budget deficit rather than on government debt when forming their policies (e.g. governments typically announce budget deficit paths as their target). The changes in the government debt ratio have an impact on the corporate sector expectations, consumption sentiment of households and on financial market conditions since it provides information about not only the current fiscal policy but also about past fiscal developments. In addition, the government debt ratio has a closer link to financial markets than the fiscal balance because it partly captures also the risk related to the refinancing of the outstanding stock of government debt, while influencing interest rates. Therefore, the government debt-to-GDP ratio is included as the third variable in our model by taking its y-o-y change.

4.5 Fiscal developments' overview

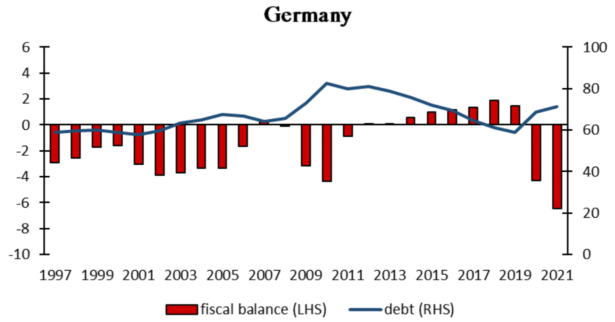
Figure 3 provides evidence about the main fiscal developments in Germany, Italy, the U.K. and France in the period 1997:1-2021:1, based on the annual national accounts data from the European Commission Ameco database. Therefore, I plot two charts: the first one with the general government debt-to-GDP ratio on the left-hand side axis and with government revenue and expenditure ratios on the right-hand side axis; the second one with the general government balance on the left-hand side axis and government debt on the right-hand side axis.

Figure 3: General government debt, revenue, expenditure
and fiscal balance developments, in % of GDP

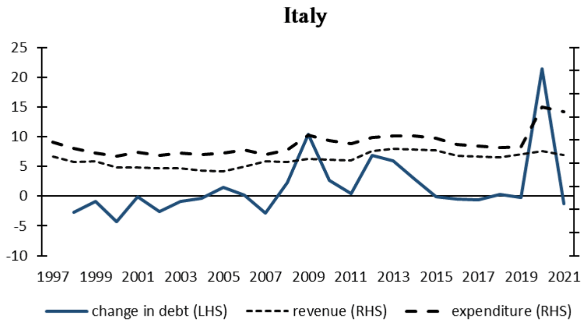
3.1 Germany – spending and revenue



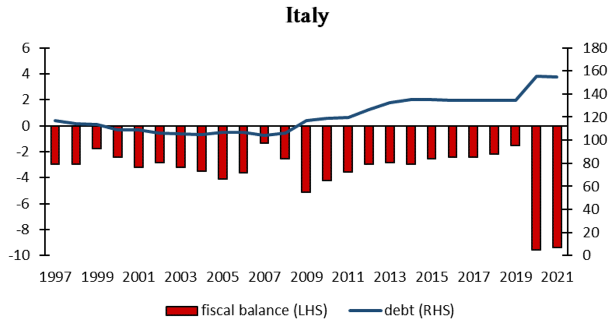
3.2 Germany – debt and deficit



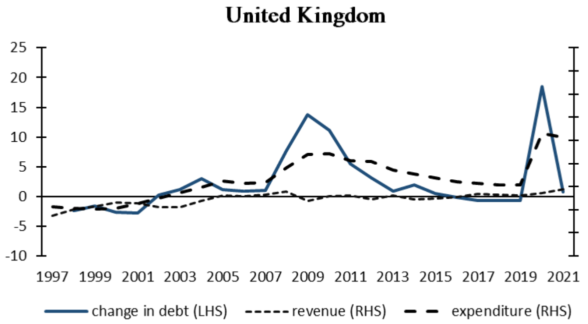
3.3 Italy – spending and revenue



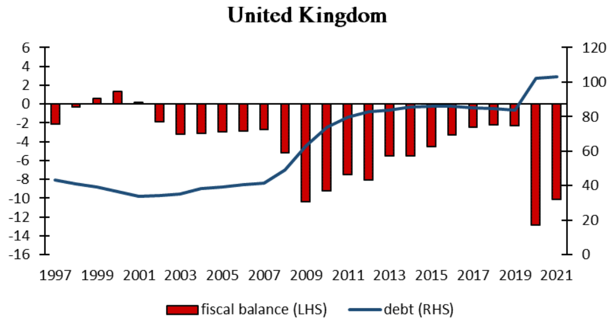
3.4 Italy – debt and deficit



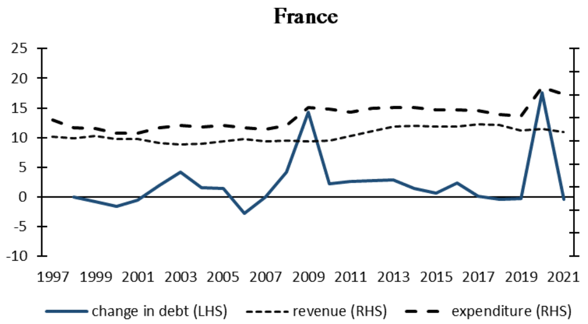
3.5 U.K. – spending and revenue



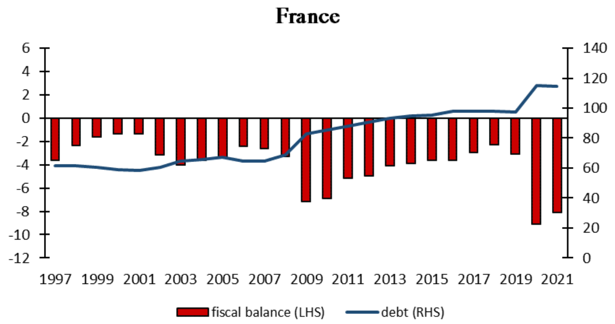
3.6 UK – debt and deficit



3.7 France – spending and revenue



3.8 France – debt and deficit



Source: European Commission Ameco

In Germany (Figure 3.1 and 3.2) the economy contracted by 4.9% in 2009-2010 as export orders fell sharply in response to the GFC and the Sovereign debt crisis. Germany balanced its budget in the two years prior to the economic crisis, but the fiscal balance quickly became negative in the period 2009-2010 as stimulus measures were adopted in response to the recession and automatic stabilizers played their role. Germany's budget deficit measured 3.15% in 2009 and 4.37% in 2010 (in % of GDP). As a result, in 2009, the German general government gross debt reached 73% of GDP, a 7.5 percentage point rise from 2008, when it was 65.5% of GDP. In 2010, during the sovereign debt crisis, debt levels reached 82.3% of GDP, a 9.4 percentage point rise from the previous year. In Germany it is also possible to identify two short periods of fiscal consolidation, notably the periods 1999-2001 and 2005-2007, both coinciding with peaks of real GDP growth rate. From a fiscal policy perspective, important changes followed the ambitious and large tax reform in 2000 in which the German government passed the most ambitious tax reform and the tax burden was reduced for both individuals and companies. As a result, the revenue-to-GDP ratio declined by almost 3 p.p. of GDP between 1999 and 2007. The changes in the German fiscal policies are more complex due to fiscal federalism, where fiscal decisions of local governments play a more important part. However, the most important period of German fiscal consolidation is the 2012-2019 when the recovery of the economic activity brought the debt ratio on a declining path that lasted until 2019 when the Covid-19 recession emerged and contributed to the ensuing fiscal deterioration. During this period, the debt ratio decreased gradually from the high levels of the Sovereign Debt Crisis, i.e. from more than 80% of GDP in 2012, to about 58% of GDP in 2019, which coincide with the peaks of the business cycle. In 2020, the global recession caused by the Covid-19 pandemic led to a massive increase in general government debt due to the scope of the measures required to stabilize the economy. As a result, the general government deficit for 2020 amounted to 4.3% of GDP and to 6.5% of GDP in 2021. The general government debt-to-GDP ratio increased to 68.7% in 2020 and to 71.4% in 2021.

In Italy (Figure 3.3 and 3.4), the general government deficit followed an opposite path to that of Germany in the period 1997-2008: while it turned from a deficit of 2.6 per cent of GDP into a marginal surplus in the former country, it remained stable in the latter, at 2.7 per cent of GDP. In the same period, the Italian public debt declined by 11.7 percentage points, to 106% of GDP, while that of Germany rose by 6.6 percentage points, to 65.5%. After 1997, the decline of the Italian debt ratio was mainly due to the downward trend in nominal interest rates, which occurred after joining the Monetary Union, and consolidation efforts, which led to a decline of interest expenditures as well. However, interest payments savings did not result in an improvement in the fiscal balance;

rather, they were largely used to reverse the increases in revenue and cuts in health and capital expenditure which had taken place in the fiscal adjustment of the years 1992-97 (Degni et al., 2001; Balassone et al., 2002, Marino et al., 2008a). Moreover, during the years 1997-2008 German and Italian fiscal policies did not fully comply with the European fiscal criteria. The net borrowing in both countries exceeded for four years in a row the 3 per cent of GDP limit set by the Treaty on the Functioning of the European Union (TFEU) (60% of GDP). In the case of Italy, the modest reduction in the debt ratio did not meet the Treaty provision that it be "sufficiently diminishing and approaching the reference value at a satisfactory pace". Moreover, approximately two thirds of the reduction were due to extraordinary operations (debt restructuring and sale of assets) which left the public sector net wealth unchanged (Momigliano and Rizza, 2007). Finally, precisely in view of its high debt level, Italy had vowed (at the ECOFIN Council held in York in March 1998; Corriere della Sera, 1998) to achieve a rapid convergence towards the Treaty benchmark debt level, by maintaining a primary surplus equal or above 5 per cent of GDP. During the GFC the debt ratio increased sharply up to 116% of GDP in 2009 and it further increased consistently to 155% of GDP up to 2020 due to the Covid-19 pandemic. This increase was accompanied by an improvement of the government fiscal balance, where government deficit reached 1.6% of GDP, recording the lowest level since 2007. This positive outcome was driven by a strong revenue increase, which outpaced real GDP growth and more than offset the substantial rise in government spending. In particular, revenues from personal income taxes and social security contributions benefitted from a sustained growth in employment and wages. In 2020, the Italian budget deficit rose to 9.5% of GDP, from 1.6% of the previous year, the lowest recorded in the last thirteen years. This sharp deterioration was the result of both the negative cyclical component resulting from the exceptional fall in GDP and the discretionary measures that were taken to mitigate the economic and social impact of the pandemic crisis (huge levels of government spending).

In the U.K. (Figure 3.5 and 3.6) government debt remained almost constant averaging 38.4% of GDP from the beginning of 1997 to 2007. Within this period, a particularly strong fiscal consolidation was carried out between 1999 and 2001 when the fiscal balance recorded surpluses of about 0.7 % of GDP on average. In the period 2001-2007, both debt ratio and fiscal deficit increased slightly, but the most severe increase was recorded during the GFC, where general government debt had a 7.6% change from its pre-crisis level of 1% of GDP, ending at 62% of GDP in 2009. In the aftermath of the financial crisis, the UK government had the largest budget deficit in its peacetime history peaking at 10.3% of GDP. Since 2009 and up to 2019, the debt ratio recorded a huge and smooth increase amounting to 83% of GDP, whilst fiscal balance improved consistently, where fiscal deficit reduced by 8% of GDP from the levels of 2009. In 2020-2021, the shock of the coronavirus pandemic had a huge effect on the UK's public finances, where the Government's budget deficit reached a peacetime record of around 12% of GDP. The deficit increased for two reasons. First and foremost, virus-related support for public services, households and businesses came at significant cost, as government expenditure increased by 11% of GDP from its pre-crisis levels of 2019. Second, the virus and the lockdowns aimed at slowing its spread took the economy into a severe recession. The contraction in economic activity following the outbreak of the pandemic, resulting in GDP being 10% lower in 2020 than in 2019, has meant less tax receipts and more government spending on areas such as unemployment benefits. In other words, the economy's automatic stabilizers took effect. As a result, debt-to-GDP ratio also peaked at 103% of GDP during these two years.

In France (Figure 3.7 and 3.8), the public finances have always been in deficit since the first oil shock (1975), regardless of up-turns or down-turns of the economic cycle. Therefore, France entered the global financial crisis in 2008 with an effective deficit of 3.2% of GDP, which peaked at 7.2% of GDP in 2009. Since 2012, the structural deficit level has gradually been reduced albeit at a slower pace than in Italy and Germany. In 2017, the nominal deficit was at 2.6% of GDP, hence falling below the under the 3% threshold of the Stability and Growth Pact for the first time since the financial crisis. However, the structural deficit remains high as reduction of the nominal deficit is due to a rise in tax receipts, rather than a reduction of public spending. As a consequence of persistent public deficits, public debt slightly increased in France from 61.4% of GDP in 1997 to 68% in 2008. However, a severe increase in the debt ratio of around 14.2% of GDP occurred in 2009, accompanied by a further deterioration of the government fiscal balance, where government deficit reached 7.17% of GDP. Since 2009, the government budget deficit decreased up to 3% of GDP in 2019, whereas the debt ratio increased again to 97.4% in the same year, resulting in the French level of indebtedness being substantially higher than the euro area average. After 3% of GDP in 2019, the general government deficit reached 9% of GDP in 2020 and debt ratio increased by 17% from the previous year's levels, amounting to 115% of GDP. The sizeable drop in economic activity following the Covid-19 pandemic weighted heavily on tax revenues and pushed up social transfers due to the response of automatic stabilizers. This macroeconomic-related impact accounted for most of the deterioration in the deficit. The temporary expenditure measures adopted to fight the pandemic and to assuage the adverse macroeconomic effects amounted to 3% of GDP and comprise, among others, additional healthcare expenditure, transfers to cover partial unemployment schemes and subsidies under the sectoral compensation fund for SMEs. These measures also include tax exemptions, mainly social security contributions. Moreover, the revenue-to-GDP ratio remained constant during the pandemic, whereas the expenditure-to-GDP ratio rose by 6 pps. to some 61.4% of GDP.

4.6 Short-term interest rate

Figure 4 exhibits the developments of the money market short-term interest rate in Germany, Italy, the U.K. and France in the period 1997:1-2021:1, based on the data provided by the International Financial Statistics (IFS) database of the International Monetary Fund (IMF). The inflation rate is the fourth variable in our model, and it is taken in levels.

Figure 4: Short-term interest rate

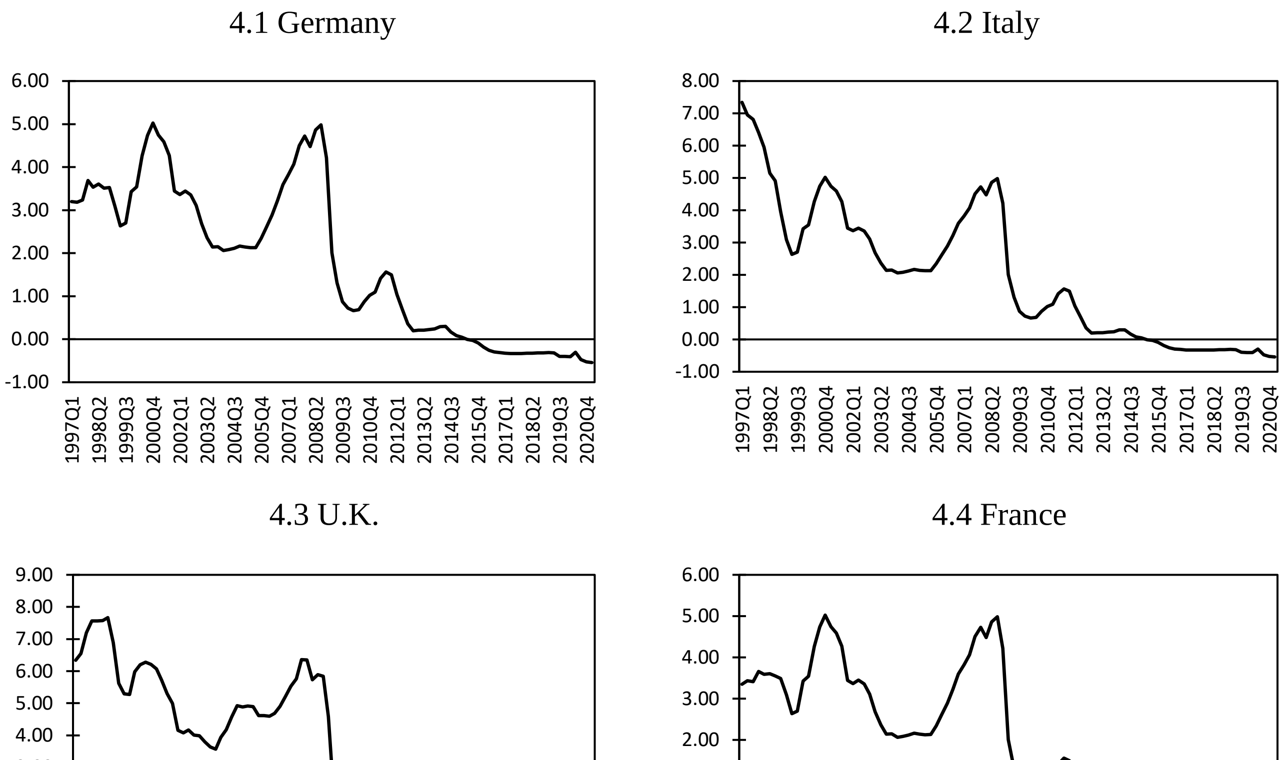


Fig. 4: Short-term interest rate of Germany, Italy, U.K. and France. Y-axis displays the values of the short-term interest rate. X-axis displays the time span, which is 1997:1-2021:1. Source: International Monetary Fund (IMF).

The money market short-term interest rate is the rate at which short-term borrowings are effected between financial institutions or the rate at which short-term government paper is issued or traded in the market. It is computed as the average of daily rates, measured as a percentage, and are based on three-month money market rates where available. Higher rates indicate a lower trust in the financial system as it suggests that the lender judges the risk of default to be higher. As such, the money market rate fulfils two key functions: first, it provides a strong gauge of macroeconomic and liquidity conditions within the financial system; second, it provides a crucial building block for the pricing of financial assets. For this reason, it has a direct impact to the financial sector. I further believe that this impact is immediate in the sense that the new changes in in the money market rates that occur during one quarter are transmitted to financial markets within the same quarter. This justifies its ordering before the financial stress variable in our model.

From figure 4, we see that short-term interest rates have been characterized by a downward trend for all countries over the entire period of consideration. A considerable fall is reported at the end of 2008 as a result of the GFC, where the major central banks provided ample liquidity in the financial system through large-scale market interventions cutting official interest rates in concert to historic lows. This reflects the exceptional depth of the recession. The consensus that the monetary policy cuts would have been temporary was abandoned. More than six years later the prospect of normalisation of interest rates to pre-crisis levels failed in most advanced economies, watching them turning even negative in Germany, Italy and France in 2015. However, during the Covid-19 pandemic, central banks had less room to reduce interest rates than in 2008 because in many countries they have nearly reached the zero lower bound. As a consequence, huge fiscal stimulus packages have been introduced to stabilize the financial system and stimulate economic activity (figure 3).

4.7 Country-Level Index of Financial Stress

The TVAR model uses as threshold variable the ECB's Country-Level Index of Financial Stress ($CLIFS$) developed by Duprey et al. (2015). The $CLIFS$ is able to identify systemic financial stress episodes for each Eurozone country, including also the UK in a transparent, reproducible and objective way. Systemic financial stress episodes are defined as periods of financial stress associated with a substantial and prolonged negative impact on the real economy, or, alternatively, as real economic stress periods which are not ordinary recessions but are also associated with high financial stress. In their paper, Duprey et al. (2015), specify that no assumptions are made about the sequence of events, i.e. whether the financial market or real economic stress occurs first. Instead, the focus of their analysis is on the detection of periods in which financial market and real economic stress mutually reinforce each other. As a result, the $CLIFS$ is able to detect the high financial stress periods associated with the recent Covid-19 recession and for this reason, it is the best leading indicator of systemic financial stress that serves our purposes. In particular, I am allowed to study the effects of fiscal policy shocks on economic activity depending on financial market conditions considering also the impact of the pandemic, which is an issue not investigated so far in macroeconomic literature.

The $CLIFS$ contains data capturing three financial market segments:

- Equity market stress (STX), which is captured by two variables. First, the monthly realized volatility ($VSTX$) is computed as the monthly average of absolute daily log-returns of the real stock price index. Second, the authors compute the cumulative maximum loss ($CMAX$) that corresponds to the maximum loss compared to the highest level of the stock market over two years.
- Bond market stress ($R10$), which is also captured by two variables. First, the monthly realized volatility ($VR10$) is computed as the monthly average of absolute daily changes in the real 10-year government bond yields. Here, changes are preferred to growth rates as for some periods very low real yields would create excessively large variations. Second, the authors compute the cumulative difference ($CDIFF$) corresponding to the maximum increase in basis points of the real government bond spread with respect to Germany over a two-year rolling window. Here, the spread is preferred to 10-year yield in order to disentangle changes in the risk profiles from changes in a proxy for the risk-free rate. For

Germany, the authors instead compute the increase of a 10-year "bond index" compared to the minimum ($CMIN$) over a two-year rolling window[6].

- Foreign exchange market stress (EER), which also relies on two variables, available only at a monthly frequency. First, the realized volatility ($VEER$) is computed as the absolute value of the monthly growth rate of the real effective exchange rate. Second, longer lasting changes in the real effective exchange rate should be associated with more severe stress due to the necessary adjustment of the real economy. Thus, the authors compute the cumulative change ($CUMUL$) over six months: if $CUMUL$ > 0, then the real effective exchange rate is volatile around a changing rate.

The $CLIFS$ is then constructed following these steps:

- First, the individual stress indicators, two for each financial market segment are standardized using the empirical cumulative density function (CDF), which transforms each variable into percentiles. The output is a unit free index where the most extreme (smallest) values, corresponding to the highest (lowest) levels of stress, are characterized by the 99th (1st) percentile.
- Second, these individual stress indicators for each financial market segment are aggregated into sub-indices by computing their average[7]. I.e.:

$$\begin{cases} I_{STX} = \dfrac{\widehat{VSTX} + \widehat{CMAX}}{2} \\ I_{R10} = \dfrac{\widehat{VR10} + \widehat{CDIFF}}{2} \\ I_{EER} = \dfrac{\widehat{VEER} + \widehat{CUMUL}}{2} \end{cases} \tag{19}$$

- Third, the sub-indices for the three financial market segments above are aggregated based on a portfolio theory approach which weights each sub-index by its cross-correlation with the others. By aggregating correlated sub-indices, the resulting index reflects increased risk due to the stronger co-movement with overall financial stress. In contrast, less correlated sub-

[6] They define a bonds index as the value after one year of holding a bond whose price is normalized to 100 at the beginning of the period. Thus, they compute the cumulative stress on a positive variable while real yields could be negative with misleading economic interpretations in the CMIN framework. The choice of a base of 100 does not impact the results as the authors subsequently use the relative ranking of the observations.

[7] For Germany the bonds sub-index is: $I_{R10} = \frac{\widehat{VR10}+\widehat{CMIN}}{2}$

indices result in a lower composite index as it captures nonsystematic components and diversifiable risk across market segments. The $CLIFS$ is therefore computed as:

$$CLIFS_t = \mathbf{I}_t * C_t * \mathbf{I}_t' \tag{20}$$

where $\mathbf{I}_t$ is the $(1x3)$ vector of standardized sub-indices and C_t is the $(3x3)$ time-varying cross-correlation matrix of the sub-indices estimated using an Exponentially Weighted Moving Average (EWMA) specification. I.e.:

$$C_t = \begin{pmatrix} 1 & \rho_{STX,R10,t} & \rho_{STX,EER,t} \\ \rho_{STX,R10,t} & 1 & \rho_{R10,EER,t} \\ \rho_{STX,EER,t} & \rho_{R10,EER,t} & 1 \end{pmatrix} \tag{21}$$

The larger value of the $CLIFS$, the higher is the stress during each period. In particular, it is bounded between 0 and 9, where the maximum is obtained when the cross-correlations of the sub-indices are all equal to unity. Moreover, the authors investigated the periods of high financial stress (when $CLIFS_{t-d} > \gamma$) obtained from a TVAR model to endogenously determine the stress threshold above which their financial stress measure significantly distorts the real economy. As a result, the authors found that the average threshold estimated with the TVAR model corresponds to the 81-th percentile of the $CLIFS$.

Chapter 5

Results

5.1) Testing and estimation results – 5.2) The effects of fiscal shocks – 5.3) Contribution of fiscal shocks

5.1 Testing and estimation results

I tested whether the data indicate the presence of a statistically significant threshold γ as defined by the values of the Country-Level Index of Financial Stress, and whether the optimal threshold values are reasonable in terms of identifying high and low stress periods that will be related to output fluctuations. Because the observed persistence of the $CLIFS$ is very low, when comparing to fluctuations of other macroeconomic variables, reasonable values of the threshold would have led to a segmentation of periods with high financial stress. Therefore, in order to avoid the presence of an implausible number of regime switches over time, I have determined the threshold from the $CLIFS$ smoothed by a 3-period moving average following Hansen's (1996) procedure described in subsection 3.3[8].

Table 1 shows our estimated threshold values that range from 0.1125 for Italy to 0.1370 for France, and the threshold is significant for all countries with a p-value often less than 0.0001 for all the Wald statistics, except for the exp-wald statistic for the U.K, whose p-value is 0.016, which is still statistically significant. Therefore, the tests for all countries reject the null hypothesis of linearity in the relationships between the times series. Since threshold effects appear to be present, a linear VAR reflecting a single regime may not be the most adequate specification to describe the dynamic behaviour of the DGP. For this reason, I proceeded with the estimation of the TVAR model.

The threshold splits the sample into a high stress regime with more than one fourth of observations (from 29 for the case of Italy to 33 for the case of France) and a low stress regime with the remaining portion. Such division seems to be well in line with the fact that the duration of

[8] In the TVAR literature is standard practice to filter the threshold variable when it is non-stationary or not sufficiently persistent. For instance, Auerbach and Gorodnichenko (2012) and Bachmann and Sims (2012) use a seven quarter moving average of GDP growth rates; Baum and Koester (2011) use the HP-filtered output gap; Atanasova (2003) uses a moving average of the spread; Balke (2000) a MA(2) of the rate of growth of the spread. Our MA(3) appears to be robust to other different filters applied to the CLIFS variable in levels.

expansions is higher than the duration of recessions. Figure 5 below shows the plotted Country-Level Index of Financial Stress along with the estimated threshold values for Germany, Italy, the U.K. and France in the period 1997:1-2021:1. The four charts show the value of the CLIFS on the y-axis and the time span on the x-axis.

We can see in Table 2 that high stress periods identified using the estimated thresholds are more frequent than recessions. However, all recessions in all countries broadly have their counterpart among the high financial stress periods. Additionally, the average annual output growth rates are lower in high stress periods than in low stress periods.

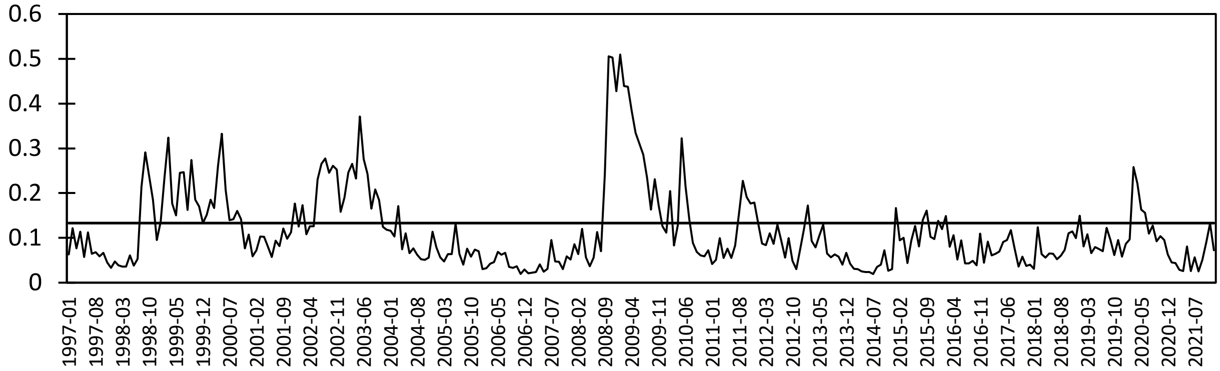
Table 1 – Thresholds per country

Threshold variable	Estimated threshold	Sup-Wald	Avg-Wald	Exp-Wald	VAR order	Sample	N. observations	
							Low stress	High stress
				Germany				
CLIFS	0.1331	206.73	120.47	99.6	1	1997Q1 - 2021Q1	66	28
		(0.000)	(0.000)	(0.000)				
				Italy				
CLIFS	0.1125	282.02	166.22	137.25	1	1997Q1 - 2021Q1	68	26
		(0.000)	(0.000)	(0.000)				
				U.K.				
CLIFS	0.1361	170.09	83.85	81.39	1	1997Q1 - 2021Q1	67	27
		(0.000)	(0.000)	(0.016)				
				France				
CLIFS	0.1370	495.07	233.17	243.83	1	1997Q1 - 2021Q1	64	30
		(0.000)	(0.000)	(0.000)				

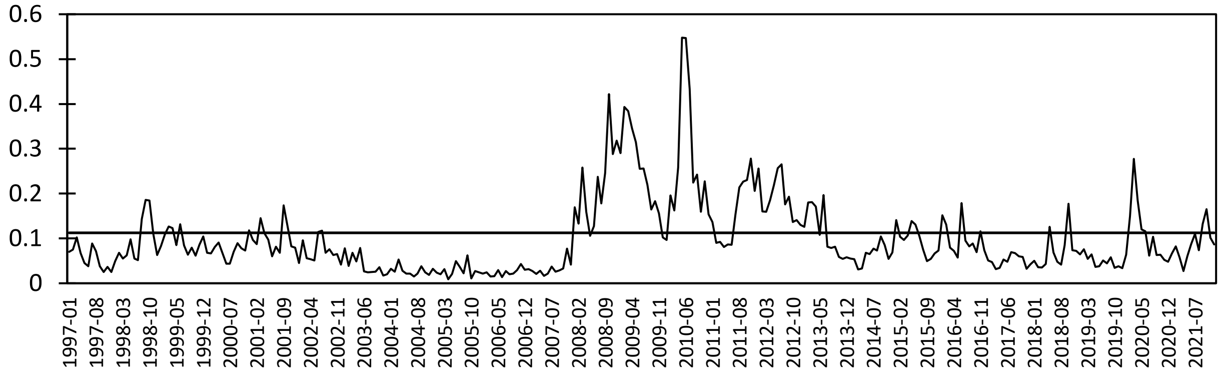
Table 1: Estimated threshold values for the CLIFS for Germany, Italy, U.K. and France, along with the results of the Wald statistics and corresponding p-values (in parenthesis), the VAR order, the sample, and the number of observations in each regime. Notes: p-values were always less than 0.0001 except for the exp-wald statistic for the U.K, whose p-value is 0.016, which is still statistically significant.

Figure 5: Country-Level Index of Financial Stress

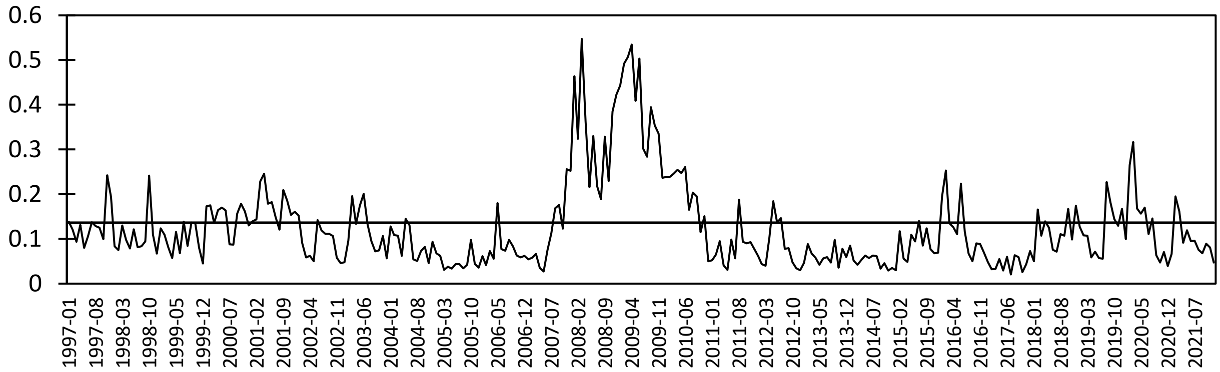
2.1 Germany



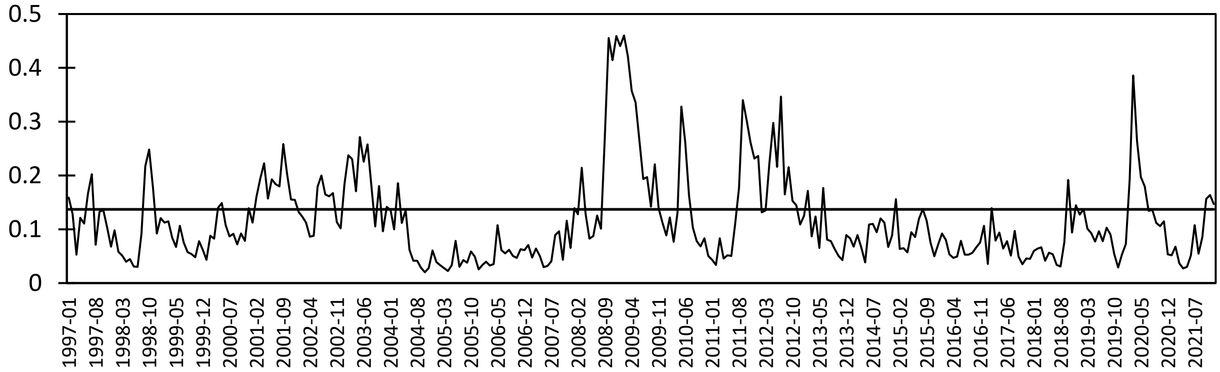
2.2 Italy



2.3 U.K.



2.4 France



Source: Duprey, T. and Klaus, B. (2015)

Table 2 – High financial stress and recessions

Germany		**ECRI Recessions**		**Annual output growth rates**		
High stress (range)		Peak	Trough		High stress	Low stress
1999Q1	2001Q1	2001Q1		**average**	**-0.07**	**1.94**
2002Q3	2004Q2		2003Q3	min	-5.69	0.44
		2008Q2		max	4.18	3.93
2009Q1	2010Q4		2009Q1	stdev	3.26	1.06
2012Q1	2012Q2					
		2019Q2				
2020Q4			2020Q2			
Italy		**ECRI Recessions**		**Annual output growth rates**		
High stress (range)		Peak	Trough		High stress	Low stress
1999Q2	1999Q3			**average**	**-1.99**	**1.27**
		2007Q3		min	-8.94	0.00
2008Q3	2013Q4		2009Q1	max	1.71	3.79
		2011Q2	2014Q4	stdev	3.69	0.94
		2019Q3				
2020Q3	2020Q4		2020Q2			
U.K.		**ECRI Recessions**		**Annual output growth rates**		
High stress (range)		Peak	Trough		High stress	Low stress
1998Q1				**average**	**0.30**	**2.51**
2000Q3	2002Q2			min	-9.40	1.47
2008Q1	2011Q1	2008Q2	2010Q1	max	3.67	4.91
2016Q3	2016Q4			stdev	4.08	0.86
		2019Q4				
2020Q2	2020Q4		2020Q2			
France		**ECRI Recessions**		**Annual output growth rates**		
High stress (range)		Peak	Trough		High stress	Low stress
2001Q3	2002Q2			**average**	**0.12**	**2.23**
2002Q4	2004Q2	2002Q3	2003Q2	min	-7.86	0.96
2008Q4	2011Q1	2008Q1	2009Q1	max	2.83	3.92
		2011Q2		stdev	3.05	0.96
2012Q1	2013Q2		2012Q4			
		2019Q4	2020Q2			
2020Q3	2021Q1					
Euro area		**CEPR Recessions**		**Annual output growth rates**		
		Peak	Trough			
		2008Q1	2009Q2			
		2011Q3	2013Q1			
		2019Q4	2020Q2			

Table 2: High financial stress periods identified through Hansen's (1996) simulation methodology, effective recession periods and some statistics of annual output growth rates for Germany, Italy, U.K. and France.

Sources: CEPR, Euro Area Business Cycle Dating Committee, http://www.cepr.org/data/dating/

Economic Cycle Research Institute (ECRI), www.businesscycle.com.

In tables 7, 8, 9 and 10 presented in appendix IV, I show the model output for both the high stress regime and low stress regime as estimated by the TVAR model for Germany, Italy, U.K. and France respectively. From these, we can see that the coefficients of the high stress regime and the low stress regime differ noticeably in both sign and size, providing indication of the existence of separate economic dynamics during the different financial regimes.

5.2 The effects of fiscal shocks

Figure 6 reports the average impulse response functions of a fiscal policy shock for the countries under analysis, both for the high and low financial stress regime. Broadly, the responses of output growth to a fiscal shock are positive in both regimes in the first 12 quarters and in all countries of our sample, although in the case of the U.K. the response is negative in the high stress regime for many quarters after the shock.

In Germany, in the high stress regime, the impulse responses are positive in the first 12 quarters after the shock and reach their peak after 7 quarters, when they start to decrease sharply. From quarter 12 on, the responses become negative reaching their minimum at quarter 20, after which they start to increase again. Overall, the effects of a fiscal shock on output growth are much higher in the high stress regime than in the low stress regime confirming the presence of significant non-linear effects. The low stress regime behaves differently, and the effect of a positive fiscal shock is slightly positive in the first 6 quarters, after which the output responses moderately decay to zero.

In Italy, when the economy is in the high stress regime, the response of output to a positive fiscal policy shock oscillates during the first 20 quarters from a positive to a negative impact with intervals of 6 quarters. Output growth then starts to decline sharply from quarter 21 to 23 and tends to die out afterwards. However, the response in the low stress regime is significant. It is positive within the first 11 quarters, after which it sharply decreases reaching negative values until quarter 20. From then on, it explodes. Such behavior leads the economy to switch to the high stress regime (figure 4) and when it happens so, the economy becomes less explosive and corrects the out of equilibrium conditions of the low stress regime.

In the U.K., fiscal policy causes an increase in output growth in the first 5 quarters when the economy is in the low stress regime. After that, output growth slightly decreases but it remains positive and never decays to zero over the entire sample path. On the other hand, the impulse response of output in the high stress regime is negative for almost the entire sample path and exhibits a sharp decrease immediately when the shock occurs reaching its minimum at quarter 4. From its minimum, output growth reverses sharply after 4 quarters and then this increase becomes more moderate after 8 quarters. Output growth breaks even at quarter 17 and stays positive for the remaining sample path. Even in the case of the U.K., the effects of a fiscal shock on output growth are much higher in the high stress regime than in the low stress regime confirming the presence of regime-dependencies of fiscal shocks.

Figure 6: Fiscal shock, Response of Output Growth

6.1 – Positive fiscal shock

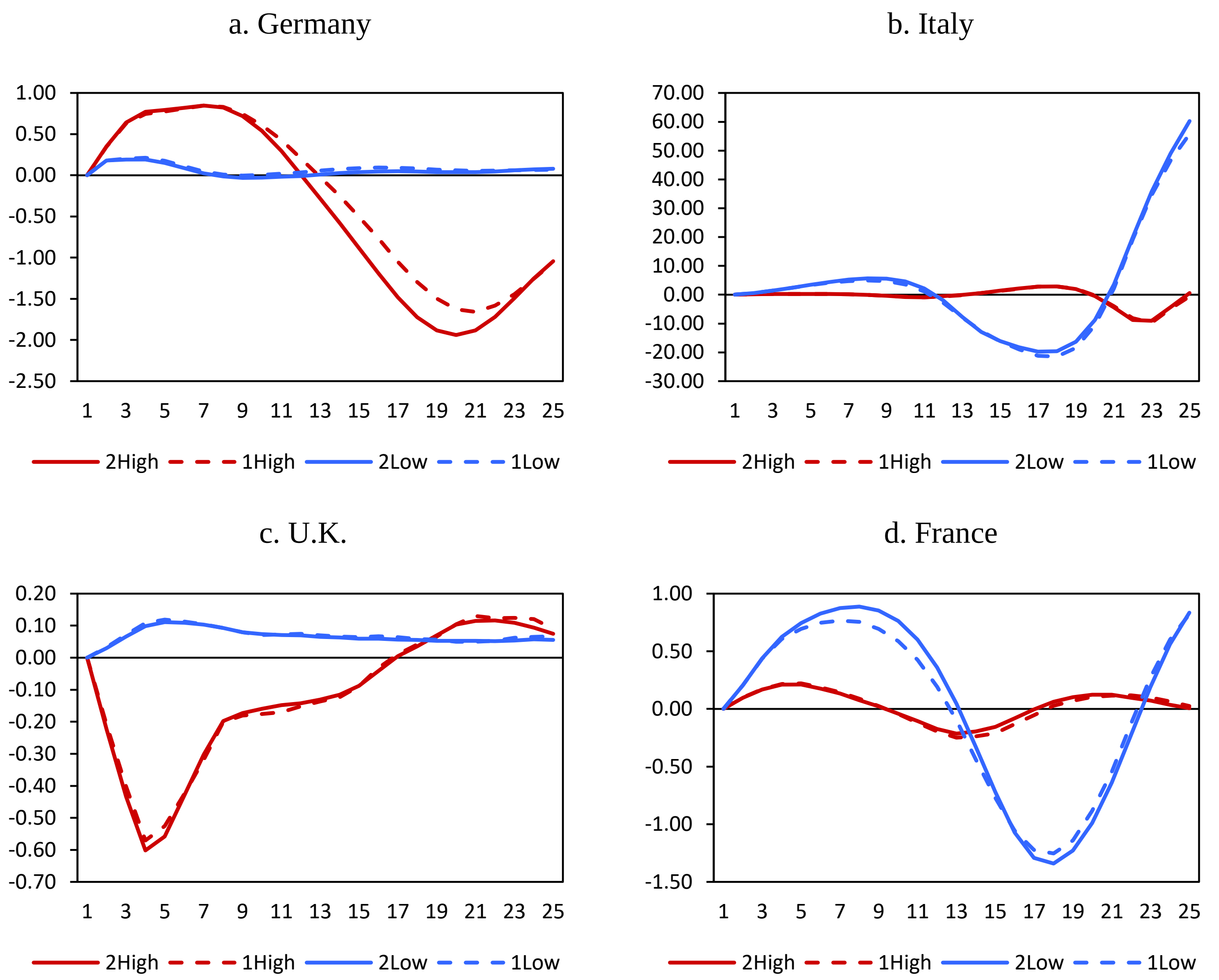


Fig. 6.1: Impact of positive fiscal shocks on output growth. Y-axis displays the values of the responses. X-axis displays the forecast horizon, which is set to 25 quarters. High stress regime (red), Low stress regime (blue). Solid line is used for the +2SD shock in the two regimes, dashed line is used for the +1SD shock in the two regimes. The impulse responses are rescaled to a fiscal shock of 1% of GDP.

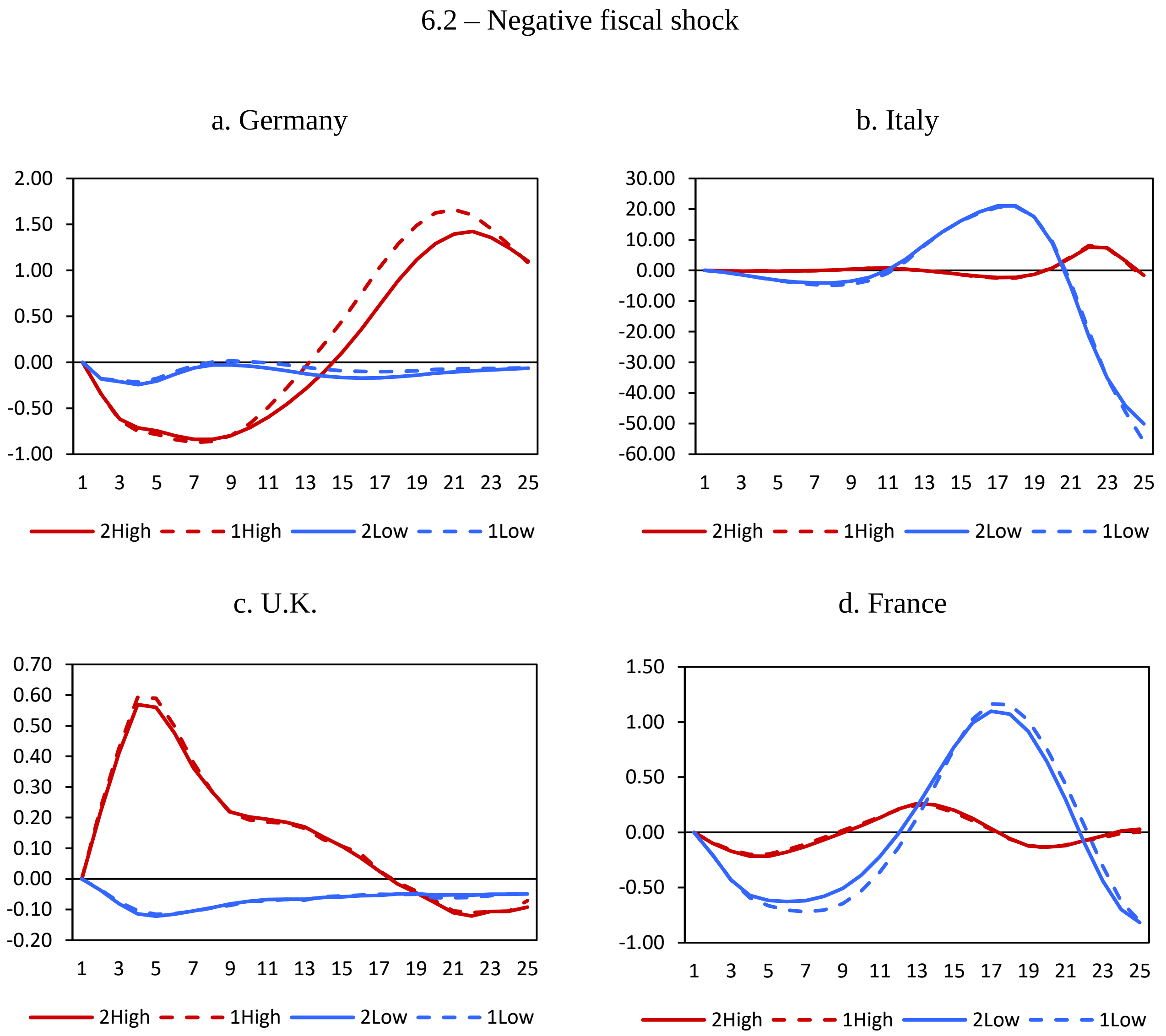


Fig. 6.2: Impact of negative fiscal shocks on output growth. Y-axis displays the values of the responses. X-axis displays the forecast horizon, which is set to 25 quarters. High stress regime (red), Low stress regime (blue). Solid line is used for the +2SD shock in the two regimes, dashed line is used for the +1SD shock in the two regimes. The impulse responses are rescaled to a fiscal shock of 1% of GDP.

In France, the results show that in the high stress regime the response of output growth to a positive fiscal policy shock is positive during the first 9 quarters, after which it decreases to negative values and after quarter 16 they start to increase again until they die out. However, in the low stress regime, the oscillating behavior of the response functions is more pronounced and it does not die out.

Table 3 reports the values of the fiscal multipliers for the responses of output at one, two and three years after a fiscal shock and also a cumulated response over three years in order to analyze more in depth the various dimensions of non-linearities in the DGP discussed in chapter 2, i.e. the size (larger vs. small shocks), direction (positive vs. negative shocks) and initial conditions (regime dependencies). The impulse responses are normalized to the same size of the initial fiscal shock set to 1% of GDP for a direct comparison between the two regimes and different signs and sizes. I use 1SD and 2SD as proxies for small and large shocks.

First of all, the values of the fiscal multipliers confirm that in the case of Germany and the U.K., fiscal policy has larger effects on output in the high stress regime than in the low stress regime indicating strong regime-dependencies of the DGP for these countries. The opposite is true for Italy and France, where the impact of fiscal policy in the low stress regime is much higher leading the economy to a switch to the high stress regime. Second, as far as the effects of the size of positive fiscal shocks are concerned, Table 3 also provides evidence of important disproportionalities between small and large shocks, in particular in Germany (in the high stress regime), Italy (in the low stress regime) and France (in the low stress regime). Conversely, one and two standard deviations shocks practically coincide in the U.K in both regimes indicating the absence of disproportionate effects. These effects can be seen in terms of the cumulative multipliers over three years. Third, the impact of fiscal shocks also differs depending on their direction (positive vs. negative shocks) indicating the presence of asymmetric effects. In Germany, in the low stress regime, the effect of a -2SD negative fiscal shock (-0.37) is twice the one of a positive +2SD fiscal shock (0.17) in absolute values. In Italy, in the high stress regime, the effect of a +1SD positive fiscal shock (-0.42) is twice the one of a negative -1SD fiscal shock (0.22) in absolute values. Moreover, in Italy, in the low stress regime, the cumulative multiplier of a +2SD shock (6.12) is three times the one of a -2SD shock (-2.63). In France, in the low stress regime, the effect of a +2SD positive fiscal shock (1.87) is significantly higher than the one of a negative -2SD fiscal shock (-1.16) in absolute terms.

Overall, for the high stress regime, the multipliers are largest in Germany with a size of the cumulative multiplier after three years of 1.60-1.78. For the low stress regime, the multipliers are largest in Italy with cumulative multipliers after three years reaching about 6.12-4.52. For the U.K. the cumulative multipliers show minor differences between signs and sizes of shock. France has the lowest effects of a fiscal policy shock on output growth in the high stress regime, with the cumulative multiplier over three years being between 0.11 (for a positive fiscal shock) and -0.04 (for a negative fiscal shock).

Table 3 – Responses of output to a 1% of GDP fiscal shock

	4 Quarters		8 Quarters		12 Quarters		Cumulative (12 Quarters)	
	2SD	1SD	2SD	1SD	2SD	1SD	2SD	1SD
				Germany				
				Positive Shock				
High	0.77	0.74	0.82	0.83	0.01	0.21	1.60	1.78
Low	0.19	0.21	-0.01	0.01	-0.01	0.04	0.17	0.26
				Negative Shock				
High	-0.71	-0.75	-0.84	-0.86	-0.46	-0.28	-2.01	-1.89
Low	-0.24	-0.22	-0.03	0.00	-0.09	-0.03	-0.37	-0.24
				Italy				
				Positive Shock				
High	0.22	0.21	-0.06	-0.05	-0.47	-0.58	-0.31	-0.42
Low	2.42	2.40	5.68	4.96	-1.98	-2.84	6.12	4.52
				Negative Shock				
High	-0.19	-0.20	0.08	0.08	0.36	0.34	0.25	0.22
Low	-2.37	-2.40	-4.06	-4.88	3.80	2.95	-2.63	-4.33
				U.K.				
				Positive Shock				
High	-0.60	-0.57	-0.20	-0.20	-0.14	-0.15	-0.94	-0.92
Low	0.10	0.11	0.09	0.09	0.07	0.07	0.26	0.28
				Negative Shock				
High	0.57	0.59	0.29	0.29	0.19	0.18	1.04	1.06
Low	-0.11	-0.10	-0.09	-0.09	-0.07	-0.07	-0.27	-0.27
				France				
				Positive Shock				
High	0.21	0.22	0.08	0.09	-0.18	-0.20	0.11	0.11
Low	0.63	0.61	0.89	0.76	0.36	0.19	1.87	1.55
				Negative Shock				
High	-0.22	-0.20	-0.07	-0.05	0.21	0.21	-0.07	-0.04
Low	-0.57	-0.59	-0.58	-0.70	-0.01	-0.14	-1.16	-1.44

Table 3: Fiscal multipliers for the responses of output growth to positive and negative fiscal shocks of sizes of 2SD and 1SD in the two regimes. The forecast horizon is set at one, two and three years after a fiscal shock and also a cumulated response over three years is provided. The impulse responses are rescaled to a fiscal shock of 1% of GDP.

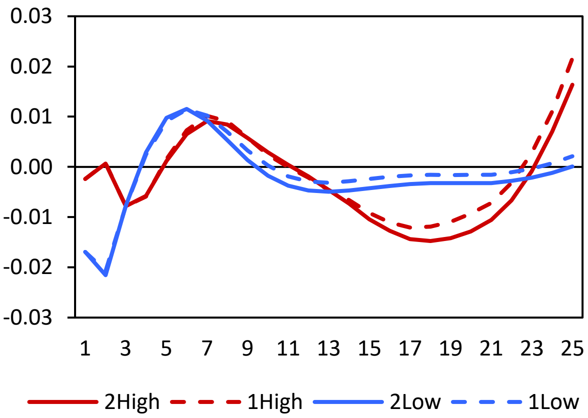
The responses of financial stress to fiscal shocks are presented in Figure 7. The results show that fiscal policy shocks immediately decrease the financial stress in all countries when the shock hits in both regimes, although in Germany, in the high stress regime, there is an initial increase in financial stress within the first 2 quarters. The effect of a fiscal shock on financial stress remains negative for about 10 quarters in the U.K. and France, and for 5 quarters in Germany, after which is turns positive. Italy is somewhat different, and the impulse response of financial stress to a fiscal shock is positive in the high stress regime. Under these circumstances, fiscal policy does not decrease financial stress in Italy for a long period (13 quarters). Still, in the high stress regime, I do not document any sharp increase in financial stress except for Germany in the long term, when financial stress starts to explode. Interestingly, in the U.K. a positive fiscal shock in the high stress regime reflects efforts to reduce financial stress, rather than to stabilize economic growth. Indeed, output growth drops significantly and so does financial stress.

In the low stress regime, the response of financial stress is negative in all countries with a hump-shaped pattern in Italy and France, whilst in Germany and in the U.K., the negative reaction of financial stress is sharper. After few quarters these responses moderately increase in Italy and in the U.K., whilst Germany and France report a faster increase. However, the increase of financial stress is higher in Italy and France, mainly when focusing on the low stress regime after 17 quarters. Interestingly, those responses for the latter two countries dramatically decrease in the long-term indicating a reduction in financial stress. A detailed investigation of simulated impulse responses reveals that this result is mainly driven by the period of the Covid-19 pandemic characterized by a huge rising debt ratio in those countries.

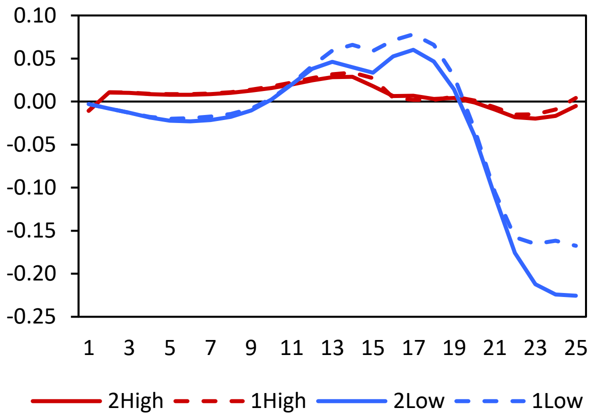
Figure 7: Fiscal shock, Response of CLIFS

7.1 – Positive fiscal shock

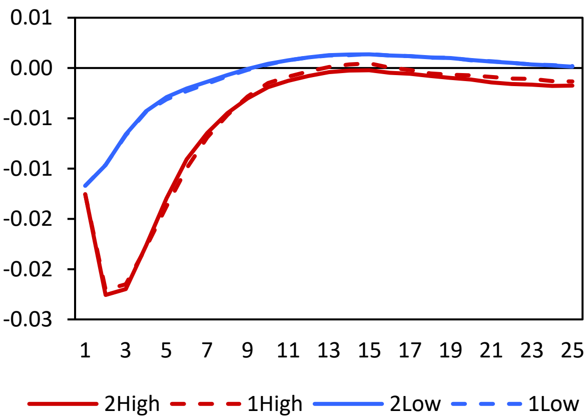
a. Germany



b. Italy



c. U.K.



d. France

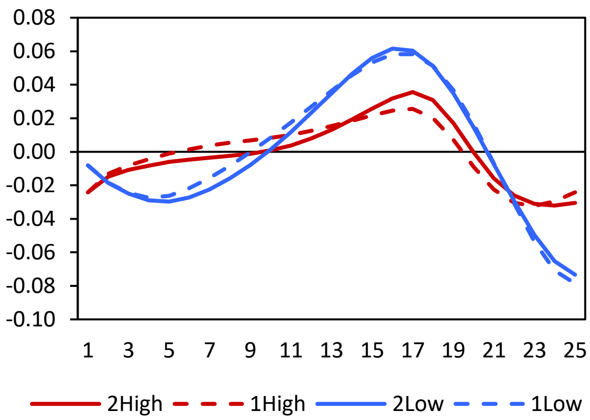


Fig. 7.1: Impact of positive fiscal shocks on financial stress. Y-axis displays the values of the responses. X-axis displays the forecast horizon, which is set to 25 quarters. High stress regime (red), Low stress regime (blue). Solid line is used for the +2SD shock in the two regimes, dashed line is used for the +1SD shock in the two regimes. The impulse responses are rescaled to a fiscal shock of 1% of GDP.

7.2 – Negative fiscal shock

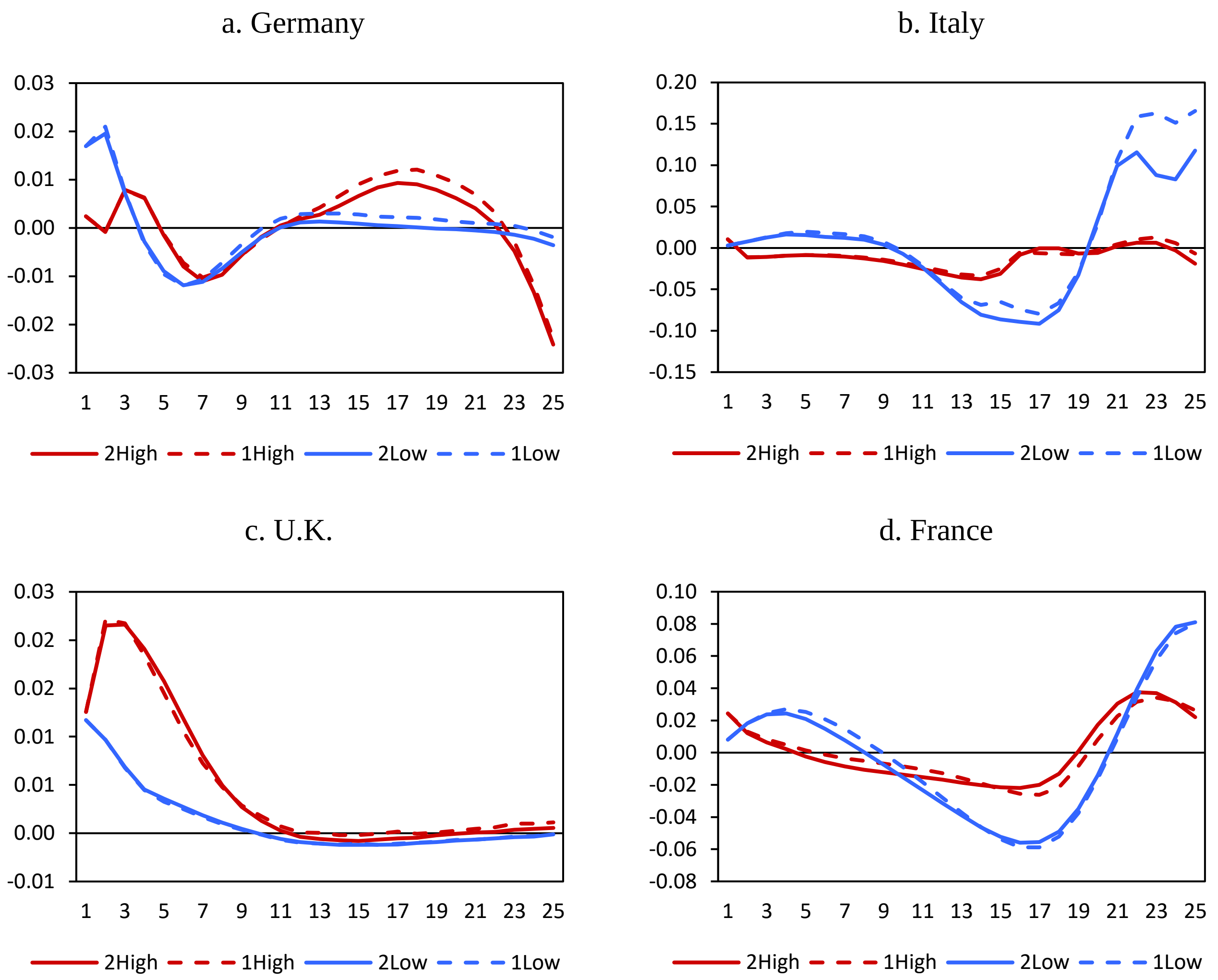


Fig. 7.2: Impact of negative fiscal shocks on financial stress. Y-axis displays the values of the responses. X-axis displays the forecast horizon, which is set to 25 quarters. High stress regime (red), Low stress regime (blue). Solid line is used for the +2SD shock in the two regimes, dashed line is used for the +1SD shock in the two regimes. The impulse responses are rescaled to a fiscal shock of 1% of GDP.

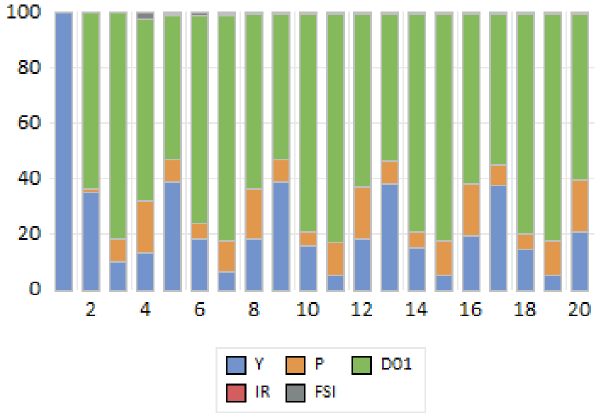
5.3 Contribution of fiscal shocks

Figures 8 shows the variance decompositions of output growth for a forecast horizon of 20 quarters for both the high and low financial stress regimes. The GFEVDs are provided for the countries under analysis.

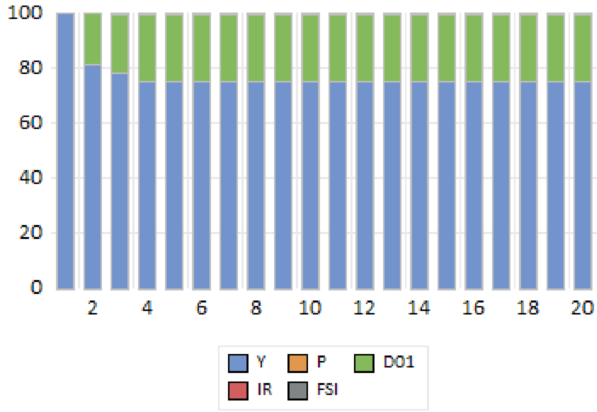
Figure 8: Generalized forecast error variance decomposition of Output Growth

8.1 – High stress regime

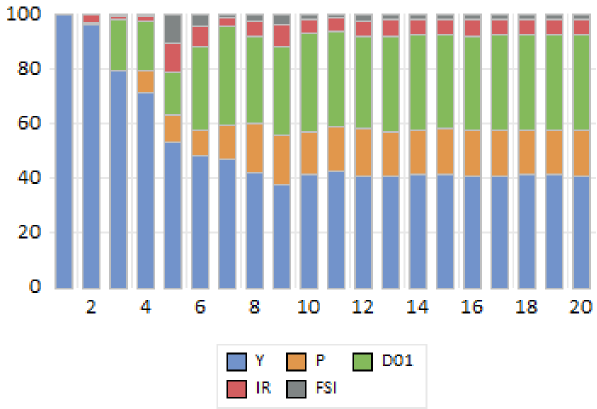
a. Germany



b. Italy



c. U.K.



d. France

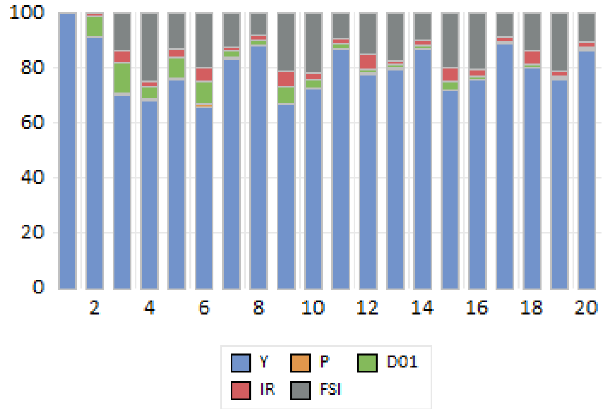
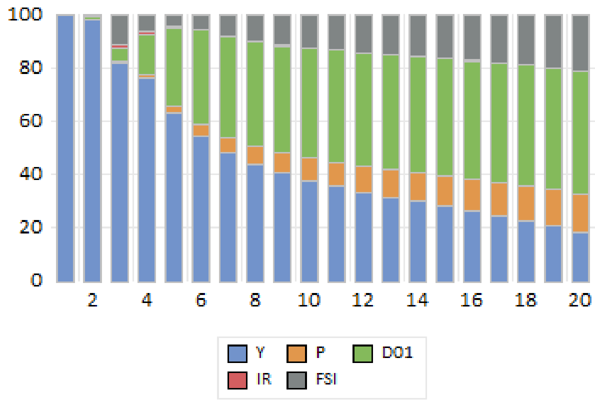


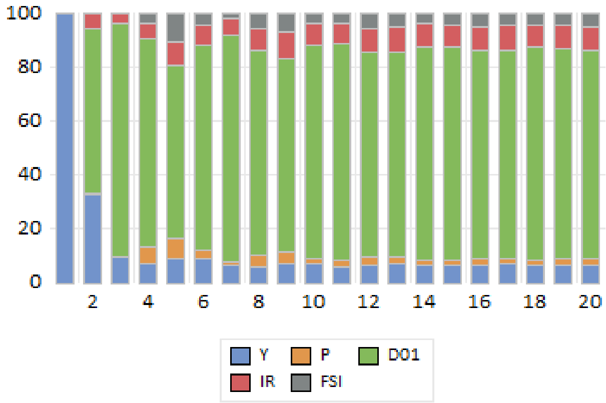
Fig. 8.1: Generalized forecast error variance decompositions of output growth in the high stress regime for Germany, Italy, the U.K. and France, considering a 1SD shock to all variables. Y-axis displays the relative contributions of the shocks, which sum to unity. X-axis displays the forecast horizon, which is set to 20 quarters. In the legend the variables are: output growth (in blue), inflation (in orange), debt-to-GDP ratio (in green), ST interest rate (in red), and the CLIFS (in grey).

8.2 – Low stress regime

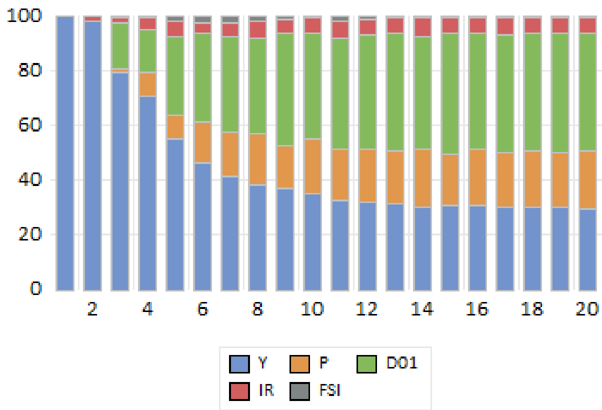
a. Germany



b. Italy



c. U.K.



d. France

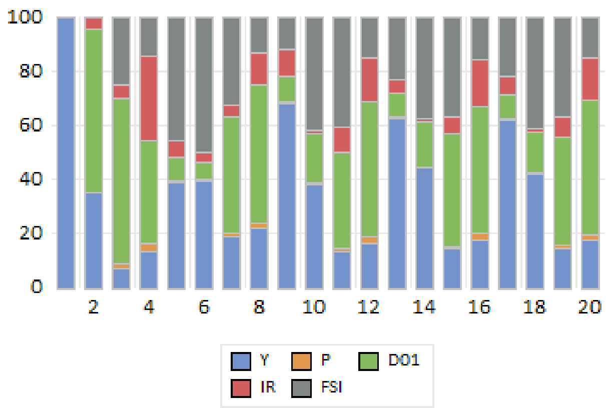


Fig. 8.2: Generalized forecast error variance decompositions of output growth in the low stress regime for Germany, Italy, the U.K. and France, considering a 1SD shock to all variables. Y-axis displays the relative contributions of the shocks, which sum to unity. X-axis displays the forecast horizon, which is set to 20 quarters. In the legend the variables are: output growth (in blue), inflation (in orange), debt-to-GDP ratio (in green), ST interest rate (in red), and the CLIFS (in grey).

In all countries, in both the high and low stress regime, and within the initial quarter, all the variation in output growth is from shocks to output growth itself.

In Germany, from the second quarter on, the contribution of the fiscal shock to the variation in output growth in the high stress regime changes fairly rapidly across each quarter over the entire forecast horizon and explains between 55% and 80% of the uncertainty of output growth. The remaining portion of the output variation over the entire forecast horizon is due to shocks to inflation and output growth itself. In the low stress regime, the contribution of the fiscal shock to the variation in output growth is considerably lower than the high stress regime. It rises in a more compact way averaging 5% within the 3rd quarter and then it homogeneously expands up to 45% in the final quarter of the forecast horizon. From quarter 3 on, the remaining portion of output variability is mainly due to shocks to output growth itself, which decreases sharply, and to shocks to inflation and financial stress. Overall, fiscal shocks play a more important role when the economy is in the high stress regime because of their higher contribution to the variation of output growth. Moreover, fiscal shocks are more important than shocks to the other variables in both regimes, as they account for the majority of the output variation.

In Italy fiscal shocks exhibit a completely different behavior. In the high stress regime approximately 80% of the output variation is explained by shocks to output growth itself constantly from the second quarter up to quarter 20. The remaining portion of variability is entirely due to fiscal shocks. Apart from the initial quarter, the system is stable as the shock contributions to output growth variability never rise nor fall during the entire forecast horizon. In the low stress regime, the variation in output growth is mostly due to fiscal shocks, whose contribution accounts for approximately 85-90% over the entire forecast horizon. Shocks to all the other variables contribute for the remaining portion of output variability. Differently from Germany, fiscal shocks play a more important role when the economy is in the low stress regime because of their higher contribution to the variation of output growth. Moreover, when the economy is in the low stress regime, fiscal shocks are more important than shocks to the other variables, as they account for the majority of the output variation, but this is not true in the high stress regime.

In the U.K. the variance decomposition of output growth is similar for both the high and low stress regime. In the high stress regime, the contribution of fiscal shocks to the variation in output growth does not change much after the fifth quarter and seems to converge at around 40% until the end of the forecast horizon. The same is true also for the low stress regime with the little difference that the contribution of fiscal shocks accounts for around 50% of the variance of output growth. The importance of the shocks to the other variables on output variation are in the following order for both regimes: inflation, interest rate and financial stress. Unlike in the case of Germany and similarly to Italy, fiscal shocks play a more important role when the economy is in the low stress regime because of their higher contribution to the variation of output growth. Moreover, in both regimes, fiscal shocks are more important than shocks to the other variables, as they account for a higher portion of the output variation.

Similar to Italy, in France and in the high stress regime, most of the variability of output growth is explained by shocks to output growth itself, whose contribution exhibits an oscillating behavior ranging from 70% to 90% over the entire forecast horizon. The remaining portion of the output variance is mostly due to financial stress shocks and to fiscal shocks. Therefore, the system is not stable in the upper regime. In the low stress regime, the variation in output growth is mostly due to fiscal shocks and financial stress shocks. However, their contribution is not homogeneous at all over the entire forecast horizon. In particular, the contribution of fiscal shocks varies from 7-10% up to 60%, whereas financial stress shocks' contributions go from 15% up to 50%. Shocks contributions to the interest rate are also present within certain quarters accounting for 0-30% of the output uncertainty. Finally, contributions of inflation shocks appear in minimal portions. As in the case of Italy, fiscal shocks are more important when the economy is in the low stress regime because of their higher contribution to the variation of output growth. Moreover, when the economy is in the low stress regime, fiscal shocks are more important than shocks to the other variables, as they account for the majority of the output variation, except in some quarters.

The variance decompositions of financial stress for both the high and low stress regimes are provided in figure 9 for the countries under analysis.

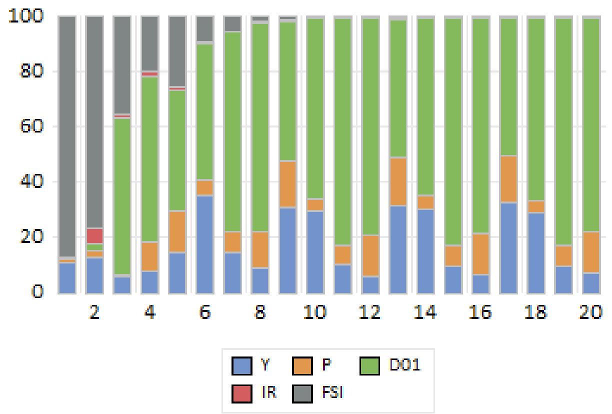
In Germany, the variation in financial stress in the high stress regime is mainly explained by shocks to the fiscal variable, whose contribution magnifies at quarter 3 and slightly increases thereafter. However, within the initial few quarters, most of the variation in financial stress is due to shocks to financial stress itself, whose contribution starts to decrease significantly from quarter 3 on. In the low stress regime, the contributions of financial stress shocks account for 80-90% of its total variation and seem to disappear at quarter 4. However, from then on, these contributions start to rise quite slowly and levels off at roughly 20%. The relative contribution of fiscal shocks stabilizes after 4 quarters and remains constant throughout the entire forecast horizon, while the variability induced by shocks to output growth and inflation decreases consistently.

In Italy, the impact of fiscal shocks to the variability in financial stress is the same as the one to the variability in output growth, with fiscal shocks contributing approximately 25% in the high stress regime and almost 90% in the low stress regime throughout the entire forecast horizon. In both regimes, the system stabilizes after 2 quarters. In the high stress regime, the remaining portion of the financial stress variation is all due to shocks to output growth, whereas in the low stress regime the remaining variance of financial stress is explained by shocks to all the other variables in the system.

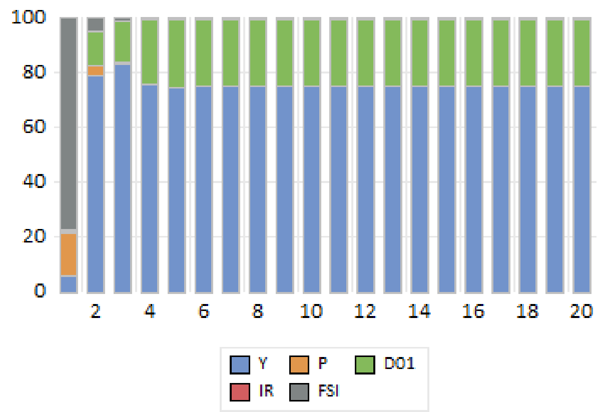
Figure 9: Generalized forecast error variance decomposition of CLIFS

9.1 – High stress regime

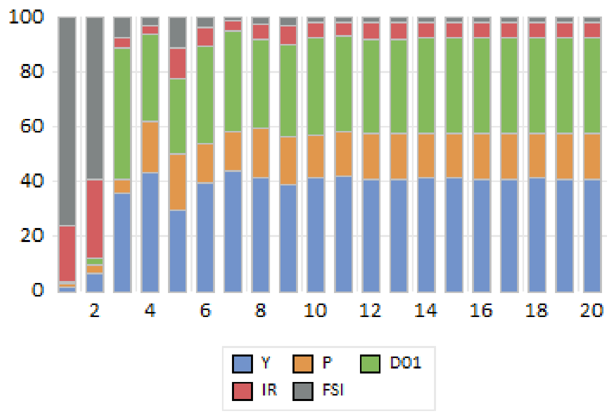
a. Germany



b. Italy



c. U.K.



d. France

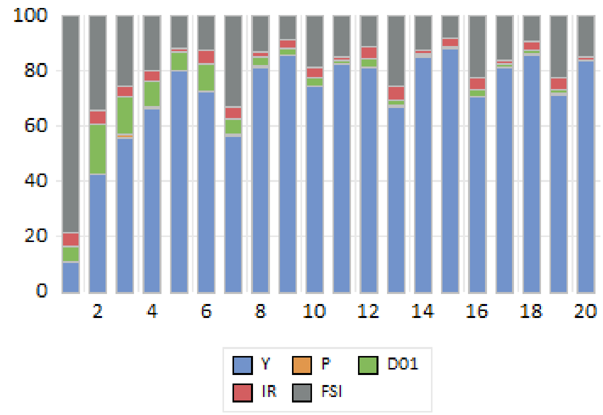
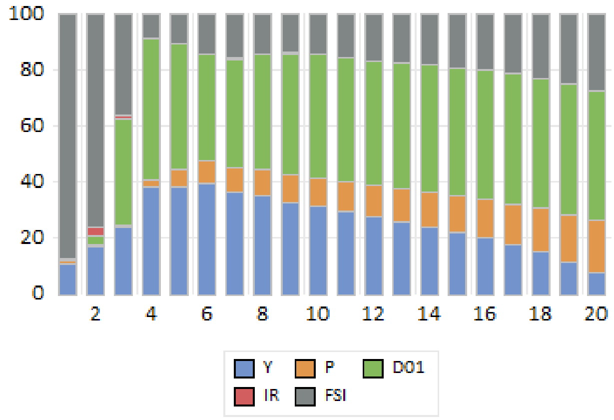


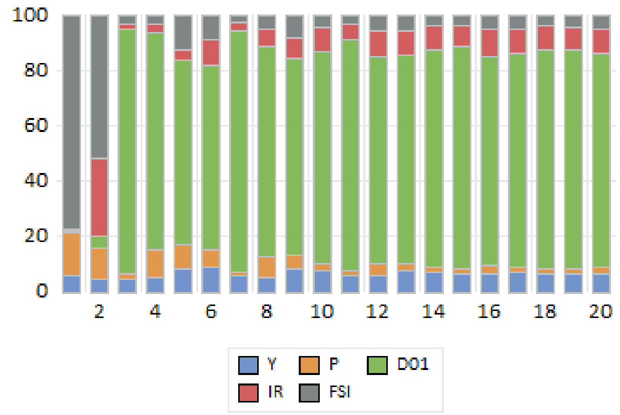
Fig. 9.1: Generalized forecast error variance decompositions of financial stress in the high stress regime for Germany, Italy, the U.K. and France, considering a 1SD shock to all variables. Y-axis displays the relative contributions of the shocks, which sum to unity. X-axis displays the forecast horizon, which is set to 20 quarters. In the legend the variables are: output growth (in blue), inflation (in orange), debt-to-GDP ratio (in green), ST interest rate (in red), and the CLIFS (in grey).

9.2 – Low stress regime

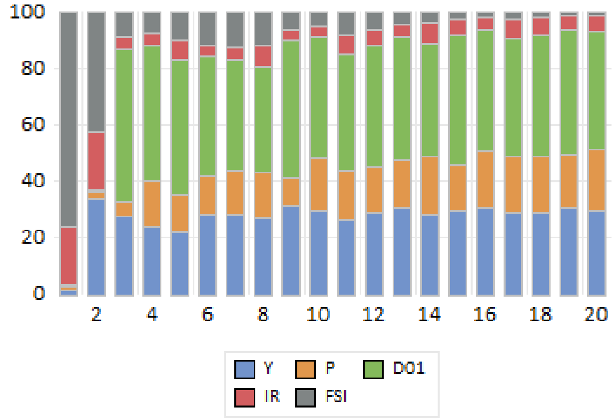
a. Germany



b. Italy



c. U.K.



d. France

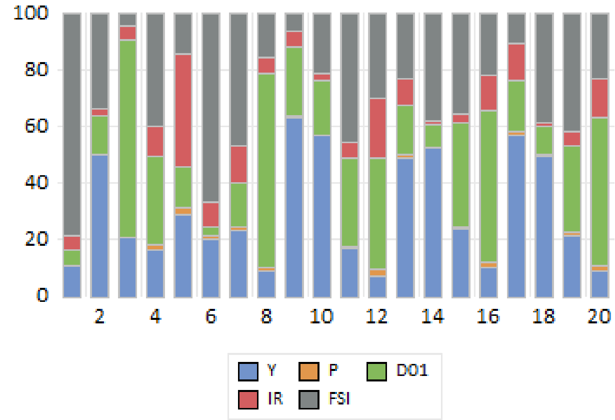


Fig. 9.2: Generalized forecast error variance decompositions of financial stress in the low stress regime for Germany, Italy, the U.K. and France, considering a 1SD shock to all variables. Y-axis displays the relative contributions of the shocks, which sum to unity. X-axis displays the forecast horizon, which is set to 20 quarters. In the legend the variables are: output growth (in blue), inflation (in orange), debt-to-GDP ratio (in green), ST interest rate (in red), and the CLIFS (in grey).

In the U.K. the variance decomposition of financial stress is similar for both the high and low stress regime. In the high stress regime, the contribution of fiscal shocks to the variation in financial stress does not change much after the 3rd quarter and seems to stabilize at around 40% thereafter until the end of the forecast horizon. In the low stress regime, the contribution of fiscal shocks accounts for around 50% of the variance of financial stress. For this reason, fiscal shocks play a more important role when the economy is in the low stress regime. Moreover, in the low stress regime, fiscal shocks are more important than shocks to the other variables, as they account for a higher portion of variability in financial stress. However, in the high stress regime, shocks to the fiscal variable and to output growth are the most important ones in equal measure.

In France, the impact of fiscal shocks to the variability in financial stress is the same as the one to the variability in output growth, with little differences in the first quarter for both regimes. In particular, in the high stress regime, most of the variability of output growth is explained by shocks to output growth itself, whose contribution exhibits an oscillating behavior ranging from 70% to 90% over the entire forecast horizon. Therefore, the system does not stabilize. In the low stress regime, the variation in financial stress is mostly due to fiscal shocks and shocks to financial stress itself, except in quarter 5, where shocks to the interest rate account for nearly 40% of the variability in financial stress. Finally, contributions of interest rate shocks appear in minimal portions in the high stress regime and in more significant portions in the low stress regime. As in the case of Italy, fiscal shocks are more important when the economy is in the low stress regime because of their higher relative contribution. Moreover, when the economy is in the low stress regime, fiscal shocks are more important than shocks to the other variables, as they account for the majority of the financial stress variation, except in some quarters.

Chapter 6

Conclusions

I analyzed the interactions between fiscal developments and economic activity in times of financial instability. The effects of fiscal policy were estimated and traced out using a threshold VAR with macro, fiscal and financial variables and with regime switching determined by a country-specific measure of financial stress. The application of a nonlinear framework with regime switching was chosen over a benchmark linear framework and its empirical adequacy was confirmed by formal nonlinearity test in the TVAR model. The use of a TVAR was also motivated by the debate on the ability of fiscal policy to shorten recessions and to facilitate a subsequent recovery. Furthermore, the identified periods of financial stress are characterized by lower growth and in a number of cases coincide with recessions.

Unlike their linear counterparts, generalized impulse responses are differences between the simulated paths of endogenous variables with and without an initial shock, either in fiscal policy or in financial stress conditions. Given its nature, this approach allows to take into account future regime switches caused by a shock on any endogenous variable and not only on financial stress. The other advantage is that the framework of generalized impulse responses can be used to recover time variance in impulse responses. Similarly, generalized forecast error variance decomposition are computed based on GIRFs and allow for the analysis of regime-dependency of variance decompositions for multivariate nonlinear models.

The empirical results and the implications of our model are the following. First, the differences among the fiscal multipliers of various sizes and signs of shocks are large in the Euro area countries (i.e. Germany, Italy and France) and small in the U.K. Moreover, the initial state of the economy matters and both multipliers and the estimated responses to fiscal shocks differ substantially across regimes. In particular, in Germany and the U.K., differences in the estimated fiscal multipliers in the two regimes indicate that fiscal policy has larger effects on output growth in the high stress regime than in the low stress regime. The opposite is true for Italy and France, where the impact of fiscal policy in the low stress regime is much higher leading the economy to a switch to the high stress regime.

Specifically, for Germany cumulative multipliers range between 1.60-1.78 in the high stress regime with large differences between signs and sizes of shock within both regimes. Moreover, the response of output growth to fiscal shocks is faster in high stress regime in comparison to the low stress regime. The U.K. has the lowest effects of a fiscal shock on output growth in the high stress regime, with the cumulative multiplier over three years being between -0.92 and -0.94. However, if the fiscal shocks occur in the low financial stress regime, the cumulative multipliers are around 0.26-0.28. The cumulative fiscal multipliers in Italy after three years are about -0.31 and -0.42 in the high stress regime. Interestingly, in the low stress regime those multipliers are much higher with a size that ranges between 4.52 and 6.12, and therefore impulse responses have an explosive behavior. Such behavior leads the economy to switch to the high stress regime and when it happens so, the economy becomes less explosive and corrects the out of equilibrium conditions of the low stress regime. Similarly, in France the cumulative fiscal multiplier is 0.11 in the high stress regime and it is much higher (1.55-1.87) when the economy is initially in the low stress regime, implying a strong rapidity to switch to the high stress regime.

Second, fiscal policy shocks immediately decrease financial stress in all countries when the shock hits in both regimes, except in Italy (in the high stress regime), where fiscal shocks slightly increase financial stress. In the high stress regime for all countries, I do not document any sharp increase in financial stress except for Germany in the long term, when financial stress starts to explode. Interestingly, in the U.K. a positive fiscal shock in the high stress regime reflects efforts to reduce financial stress, rather than to stabilize economic growth. Indeed, output growth drops significantly and so does financial stress. In the low stress regime, the response of financial stress is negative in all countries immediately when the shock hits the economy. After few quarters these responses increase. However, the increase of financial stress is higher in Italy and France after 17 quarters, mainly when focusing on the low stress regime. Interestingly, those responses for the latter two countries dramatically decrease in the long-term indicating a reduction in financial stress. A detailed investigation of simulated impulse responses reveals that this result is mainly driven by the period of the Covid-19 pandemic characterized by a huge rising debt ratio in those countries.

Third, in Germany and in the U.K. fiscal shocks play a more important role when the economy is in the high stress regime because they contribute more to the variation of output growth. Furthermore, fiscal shocks are more important than shocks to the other variables in both regimes for the same reason. However, the relative contribution of fiscal shocks on output growth remains broadly constant over time with some little exceptions.

Therefore, I have found evidence of nonlinearities in the effects of a fiscal shock depending on the initial conditions, determined by the existence of financial stress. In addition, both the multipliers and the nature of these nonlinearities vary across countries and evolve over time. Finally, the estimated thresholds also match economic recessions, and the effectiveness of fiscal policy in the context of different financial stress regimes also differs across country, naturally something to bear in mind by policy makers.

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Appendix

Appendix I: Data description and sources

Variables in Threshold VAR

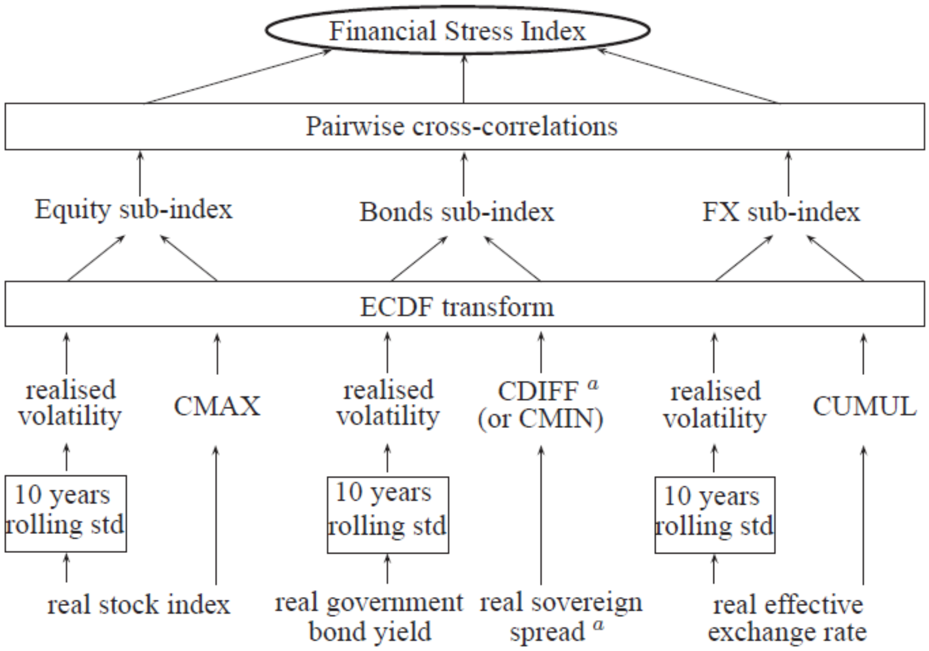
y_t	GDP, annual growth rate of the log of the real GDP (Y) used: $y_t = \log(Y_t) - \log\,(Y_{t-4})$
p_t	Price level (P), annual growth rate of logs used: $p_t = \log(P_t) - \log\,(P_{t-4})$:
f_t	Annual change in the debt to GDP ratio (D_t): $f_t = \log(D_t) - \log\,(D_{t-4})$
i_t	Short-term interest rate.
s_t	Country-Level Index of Financial Stress.

Financial stress variable

Country-Level Index of Financial Stress ($CLIFS$) components:

- Equity market stress (STX): Monthly realized volatility ($VSTX$) computed as the monthly average of absolute daily log-returns of the real stock price index; Cumulative maximum loss ($CMAX$) that is the maximum loss compared to the highest level of the stock market over two years.
- Bond market stress ($R10$): Monthly realized volatility ($VR10$) computed as the monthly average of absolute daily changes in the real 10-year government bond yields; Cumulative difference ($CDIFF$) corresponding to the maximum increase in basis points of the real government bond spread with respect to Germany over a two-year rolling window. For Germany, the increase of a 10-year "bond index" is computed compared to the minimum ($CMIN$) over a two-year rolling window.
- Foreign exchange market stress (EER): Realized volatility ($VEER$) computed as the absolute value of the monthly growth rate of the real effective exchange rate; Cumulative change ($CUMUL$) over six months.

A graphical representation of the construction of the $CLIFS$ is provided below. The authors use the sovereign spread with respect to Germany to compute the $CDIFF$. For Germany, however, the authors use the real 10-year government bonds yield to compute the $CMIN$.



Source: Duprey, T. and Klaus, B. (2015)

Data Sources

Germany

- Real GDP: International Monetary Fund (IMF), International Financial Statistics (IFS).
- GDP deflator: International Monetary Fund (IMF), International Financial Statistics (IFS).
- Government debt: Statistische Angaben: Umrechnungsart: Endstand, Euro, Millionen, Bundesbank. SeriesBQ1710, BQ1720, Central, state and local government debt; Total debt (excluding hospitals).
- Short-term interest rate: Money market rates, International Monetary Fund (IMF), International Financial Statistics (IFS).
- Country-level index of financial stress: European Central Bank (ECB), Statistical Data Warehouse.

Italy

- Real GDP: International Monetary Fund (IMF), International Financial Statistics (IFS).
- GDP deflator: International Monetary Fund (IMF), International Financial Statistics (IFS).
- Government debt: Federal Debt held by the Public, FRED.
- Short-term interest rate: Money market rates, International Monetary Fund (IMF), International Financial Statistics (IFS).

- Country-level index of financial stress: European Central Bank (ECB), Statistical Data Warehouse.

United Kingdom

- Real GDP: International Monetary Fund (IMF), International Financial Statistics (IFS).
- GDP deflator: International Monetary Fund (IMF), International Financial Statistics (IFS).
- Government debt: Since 2000 Quarterly Government Debt (Maastricht Debt) for General Government, Eurostat; older data from other sources, merged using growth values in overlapping periods (Public sector debt, National Statistics, series BKQK; Quarterly amounts outstanding of General Government sterling and all foreign currency consolidated gross debt total (in sterling millions), Bank of England, series DPQG004).
- Short-term interest rate: End of quarter Sterling interbank lending rate, 1 month, average; Bank of England, series IUQVNEA.
- Country-level index of financial stress: European Central Bank (ECB), Statistical Data Warehouse.

France

- Real GDP: International Monetary Fund (IMF), International Financial Statistics (IFS).
- GDP deflator: International Monetary Fund (IMF), International Financial Statistics (IFS).
- Government debt: Federal Debt held by the Public, FRED.
- Short-term interest rate: Money market rates, International Monetary Fund (IMF), International Financial Statistics (IFS).
- Country-level index of financial stress: European Central Bank (ECB), Statistical Data Warehouse.

Appendix II: Computation of the Generalized impulse response functions

The algorithm for computing generalized impulse response functions (GIRFs) follows the steps suggested by Koop, Pesaran and Potter (1996), and it is designed to simulate the effects of orthogonal structural shocks as in Kilian and Vigfusson (2011). GIRF is defined as the difference between the forecasts of variables with initial shock U_t and without initial shock into a variable of interest. Following Koop, Pesaran and Potter (1996), the generalized impulse response functions (GIRFs) are given by:

$$GIRF_y\left(l, \delta_{jt}, \Omega_{t-1}\right) = E\left(Y_{t+l} \middle| U_{jt} = \delta_{jt}, \Omega_{t-1}\right) - E\left(Y_{t+l} \middle| U_{jt}^0 = \delta_{jt}^0, \Omega_{t-1}\right) \tag{A1}$$

where Y_{t+l} is a vector of variables at horizon l, Ω_{t-1} is the information set available before the time of shock U_{jt}. $U_{jt} = \delta_{jt}$ denotes the structural shock to the j-th equation hitting at time t that the expectations are conditioned on, and $U_{jt}^0 = \delta_{jt}^0$ denotes stochastic disturbance at time 0 that would occur under the no shock scenario. GIRFs are computed by simulating the model with and without the shock. Given our model (5), I compute the GIRFs as follows:

1. Pick a history Ω_{t-1}.
2. The shocks for the periods from 0 to q are drawn from the residuals of the estimated VAR model.
3. For each initial value this sequence of shocks is fed through the model to produce forecasts conditional on initial conditions.
4. Repeat step 2 with the initial shock into one variable equal to +/- 1 or +/-2 SD to get forecasts if there was an initial shock.
5. The difference between the forecasts from step 2 and 3 is the impulse response function. Repeat this 500-times and derive an average impulse response for this particular initial condition.
6. Repeat steps 2-4 for each initial conditions. Final impulse responses are average impulse responses over initial conditions of each regime.

Appendix III: Computation of the Generalized forecast error variance decompositions

The algorithm for the computation of the state-dependent Generalized Forecast Error Variance Decomposition (GFEVD) for our TVAR model is similar to the one proposed in Lanne and Nyberg (2016). The innovations are: i) it is designed to simulate the importance of an orthogonal structural shock, and ii) it considers a one standard deviation shock in each variable. In particular, conditional on a specific initial history Ω_{t-1} and a forecast horizon of interest h, the $GFEVD_{ij}$ that refers to a variable i and a shock j whose size is δ_{jt} is given by:

$$GFEVD_{ij}(h, \Omega_{t-1}) = \frac{\sum_{l=1}^{h} GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)^2}{\sum_{j=1}^{k} \sum_{l=1}^{h} GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)^2} \quad i, j = 1, \dots, k \qquad \text{(A2)}$$

where h is an indicator that keeps track of the forecast errors, and k denotes the number of shocks to the i-th variable in the vector Y_t. Ω_{t-1} is the information set available before the time of shock δ_{jt}. The $GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)$ are the generalized impulse response functions à la Koop, Pesaran, and Potter (1996) computed by considering an orthogonal shock as in Kilian and Vigfusson (2011). Given our TVAR model (5), I compute the state dependent GFEVD for the high and low stress regime by following the steps indicated below. In particular, we:

1. Consider an orthogonal shock equal to a standard deviation in each variable of the estimated TVAR model. Therefore, I take a vector of shocks equal to $(\delta_{1t}, \delta_{2t}, \dots, \delta_{kt}) = (1,1, \dots, 1)$ from the residuals of the estimated model.
2. Pick a history Ω_{t-1} from among the set of all histories.
3. Compute the $GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)$ for each δ_{jt} ($j = 1, \dots, k$) and for each $l \leq h$ according to the steps of the algorithm in the previous section.
4. Plug the GIRFs computed in step 3 into equation (A2) to obtain $GFEVD_{ij}(h, \Omega_{t-1})$ for the particular forecast horizon h and history Ω_{t-1} considered.
5. Repeat Steps 2-4 for all the histories, distinguishing between the histories belonging to the high stress regime and the low stress regime.
6. Finally, compute the state dependent GFEVD for the high and low stress regime by computing the average of the $GFEVD_{ij}(h, \Omega_{t-1})$ across all the histories relevant for the two regimes.

Appendix IV: Preliminary analysis

Table 4: Unit root tests

4.1 Germany

Variables	ADF		Phillips-Perron	
	t-statistic	p-value	t-statistic	p-value
Output growth	-3.44041	0.009688*	-3.72491	0.0051*
Inflation	-3.10398	0.02629*	-3.22783	0.0213*
Debt ratio	-2.76349	0.06363	-2.0154	0.2799
ST interest rate	-1.57482	0.4955	-1.15163	0.6925
CLIFS	-3.62032	0.005412*	-3.82367	0.0038*

4.2 Italy

Variables	ADF		Phillips-Perron	
	t-statistic	p-value	t-statistic	p-value
Output growth	-4.10245	0.0009597*	-4.23929	0.001*
Inflation	-1.75149	0.4052	-3.66866	0.0061*
Debt ratio	-1.67463	0.4443	-1.03215	0.7392
ST interest rate	-2.31589	0.1669	-2.31057	0.1708
CLIFS	-3.45467	0.009258*	-3.32402	0.0164*

4.3 U.K.

Variables	ADF		Phillips-Perron	
	t-statistic	p-value	t-statistic	p-value
Output growth	-4.19846	0.000659*	-4.16334	0.0012*
Inflation	-5.29475	0*	-5.32357	0*
Debt ratio	-2.3832	0.1465	-1.08073	0.7209
ST interest rate	-1.68717	0.4379	-1.19652	0.6735
CLIFS	-3.23229	0.01822*	-3.12543	0.028*

4.4 France

Variables	ADF		Phillips-Perron	
	t-statistic	p-value	t-statistic	p-value
Output growth	-4.81889	0*	-4.88266	0*
Inflation	-3.00191	0.03473*	-4.17128	0.0012*
Debt ratio	-2.67684	0.07806	-1.81962	0.3691
ST interest rate	-1.64706	0.4584	-1.16798	0.6857
CLIFS	-4.08582	0.001023*	-4.1602	0.0013*

Table 4: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests of the model's variables for Germany, Italy, U.K. and France. T-statistics and corresponding p-values are reported. * denotes rejection of the null hypothesis of unit root for both tests.

Table 5: Cointegration tests

Countries	Specification	Relevant test statistic		N. cointegrating relationships
		Trace	Max Eigenv.	
Germany	R	3.5464	3.2421	0
	U	10.909	19.232	2-3
Italy	R	9.4778	9.4756	1
	U	6.4667	14.109	3-4
U.K.	R	3.8977	3.8764	0
	U	8.7404	6.3822	3
France	R	7.4446	7.2794	0
	U	10.217	7.2908	3

Table 5: Trace and Maximum Eigenvalue tests for the restricted (R) and the unrestricted model (U) for Germany, Italy, U.K. and France. The unrestricted model includes all 5 endogenous variables. The restricted model includes only the non-stationary variables resulting from Table 4.

Table 6: Lag Length Selection

6.1 Germany

lags	loglik	p(LR)	AIC	**SIC**	HQC
1	-225.58		5.496345*	**6.313312***	5.826213*
2	-205.24	0.0248	5.596554	7.094328	6.201313
3	-184.995	0.02596	5.698815	7.877396	6.578464
4	-159.961	0.00209	5.698089	8.557476	6.852628

6.2 Italy

lags	loglik	p(LR)	AIC	**SIC**	HQC
1	-292.143		6.927815	**7.744782***	7.257683*
2	-259.169	0.00002	6.756331*	8.254104	7.361089
3	-246.088	0.39898	7.01265	9.191231	7.892299
4	-217.665	0.00028	6.939034	9.79842	8.093572

6.3 U.K.

lags	loglik	p(LR)	AIC	**SIC**	HQC
1	-328.28		7.70495	**8.521917***	8.034818*
2	-308.202	0.0281	7.810791	9.308565	8.415549
3	-283.182	0.00211	7.810368	9.988948	8.690016
4	-249.709	0.00001	7.628153*	10.48754	8.782692

6.4 France

lags	loglik	p(LR)	AIC	**SIC**	HQC
1	-328.28		7.70495	**8.521917***	8.034818*
2	-308.202	0.0281	7.810791	9.308565	8.415549
3	-283.182	0.00211	7.810368	9.988948	8.690016
4	-249.709	0.00001	7.628153*	10.48754	8.782692

Table 6: Lag length selection for VAR models for Germany, Italy, U.K. and France. * denotes the value for which the criterion is minimized. The bold format indicates the lag and the criterion chosen.

Appendix V: TVAR Estimation Output

Table 7 – Estimation output for Germany

Table 7.1 – High stress regime

High stress regime			Quarterly frequency		
Std Errors in blue & p-vlaues of the t-stat in red			Included observations: 28		
	Output growth (y)	Inflation (π)	GDP ratio (f)	ST Interest rate (i)	CLIFS (s)
Constant	0.22023928	0.900350543	4.595185327	-0.198034854	-0.08107356
	2.61983645	0.762872392	3.014193153	0.771771271	0.10999564
	0.93398595	0.25416763	0.14576703	0.80056882	0.47113585
Output growth (1)	0.89539645	-0.341340724	-0.19208364	0.115546217	0.0202556
	0.45756864	0.133239799	0.526445175	0.134794037	0.01921134
	0.06699416	0.02021054	0.71970852	0.40325414	0.30647515
Output growth (2)	0.14102026	0.230842755	0.178456789	-0.051496137	-0.0103323
	0.35623845	0.103733376	0.409862035	0.104943422	0.01495692
	0.69713291	0.03988157	0.66874476	0.62990983	0.4990132
Inflation (1)	0.20141141	0.302531977	0.817876557	-0.122525323	0.02366646
	1.09844451	0.319856987	1.263790316	0.323588108	0.04611895
	0.85668426	0.35748357	0.52617039	0.70963799	0.61444263
Inflation (2)	-0.12663092	0.32566401	-1.290279964	-0.07223883	0.01752723
	1.06066675	0.308856448	1.220325969	0.312459248	0.04453283
	0.90636745	0.30644748	0.30515781	0.81992346	0.69878365
GDP ratio (1)	0.37306844	0.030890835	0.967952495	0.006845733	0.00581006
	0.29974641	0.087283411	0.344866405	0.088301569	0.01258506
	0.23015984	0.72775462	0.01213189	0.93910969	0.65017555
GDP ratio (2)	0.13145791	0.036267846	-0.441409055	0.006037314	-0.00288394
	0.20710785	0.06030791	0.238283221	0.0610114	0.00869557
	0.53405344	0.55552353	0.08140461	0.92233237	0.74420204
ST interest rate (1)	0.10376771	0.249938624	-0.565198994	1.098748761	-0.04783004
	1.02682162	0.299001057	1.18138623	0.302488894	0.04311182
	0.92068738	0.41479947	0.63844606	0.00205907	0.28268787
ST interest rate (2)	0.08289786	-0.273705277	-0.929672425	-0.134040844	0.09180721
	1.19263396	0.347284092	1.372157838	0.351335149	0.05007356
	0.94539618	0.44147216	0.50718914	0.7075451	0.08430573
CLIFS (1)	-12.20949071	-0.347122597	5.899423446	-2.113054896	0.50634706
	4.85041942	1.412397733	5.580539576	1.428873302	0.20364821
	0.02215315	0.80880424	0.30523844	0.1574774	0.02359594
CLIFS (2)	4.98173036	-2.308313879	0.054247715	3.278051909	-0.05013193
	5.66052787	1.648293899	6.512591406	1.667521189	0.23766117
	0.39108663	0.17937325	0.99345093	0.06586997	0.83544296

Table 7.1: Estimation output in the high stress regime for Germany. Standard errors reported in blue, p-values of the t-statistic reported in red.

Table 7.2 – Low stress regime

Low stress regime			Quarterly frequency		
Std Errors in blue & p-vlaues of the t-stat in red			Included observations: 66		
	Output growth (y)	Inflation (π)	GDP ratio (f)	ST Interest rate (i)	CLIFS (s)
Constant	1.43249485	0.538700997	0.492536553	0.084220532	0.000450332
	1.23231366	0.253155945	0.975220909	0.143312048	0.039743778
	0.25007468	0.03783874	0.61554067	0.55915741	0.99100046
Output growth (1)	0.52098154	0.0919896	-0.258729318	0.01511279	-0.006396937
	0.21236759	0.043626976	0.168062177	0.024697312	0.006849141
	0.0173568	0.03955258	0.12941978	0.54311184	0.35439847
Output growth (2)	0.21218511	-0.071640349	-0.138895059	0.006373134	0.010685264
	0.29002731	0.059580722	0.229520054	0.033728757	0.009353772
	0.46751622	0.23435658	0.54756535	0.85082555	0.25825807
Inflation (1)	-0.89761439	0.705114579	0.847423881	-0.045359469	-0.000119386
	0.77214701	0.158623256	0.611057014	0.089796918	0.024902782
	0.25005528	0.00004302	0.17109308	0.615483	0.99619224
Inflation (2)	0.03063786	0.134187809	-0.922265294	0.049568979	0.004905949
	0.70472298	0.144772242	0.557699393	0.081955833	0.022728267
	0.96548032	0.35803377	0.10388645	0.54778226	0.8299014
GDP ratio (1)	0.11991305	-0.020183283	1.063282764	-0.001368216	-0.003834893
	0.20083135	0.041257069	0.158932695	0.023355703	0.006477082
	0.55290193	0.62663989	0.00000001	0.95349763	0.55622915
GDP ratio (2)	-0.2001088	0.041821468	-0.281333071	0.01590261	0.003822652
	0.20312332	0.041727911	0.160746497	0.023622248	0.006551001
	0.32886003	0.32061588	0.08566663	0.50363609	0.56192748
ST interest rate (1)	1.51199763	-0.419697402	-0.230471775	1.270309139	0.00311064
	1.34787288	0.276895439	1.066671459	0.156751019	0.043470718
	0.26683573	0.1353155	0.82973541	0	0.94321393
ST interest rate (2)	-1.62434284	0.378614537	0.382585759	-0.285264112	0.004596715
	1.33355894	0.273954906	1.05534378	0.155086378	0.043009074
	0.22840418	0.17254928	0.71835107	0.07125796	0.91527483
CLIFS (1)	-10.87564739	0.089196964	-6.220607991	-1.04624239	1.011009103
	7.48670027	1.538003467	5.924779432	0.870666602	0.241456182
	0.15199917	0.95396257	0.29834159	0.23464534	0.00010285
CLIFS (2)	10.76998987	-2.883954534	3.853744214	-0.055737287	-0.235134405
	8.8241813	1.812764093	6.983227052	1.0262091	0.284591749
	0.22747915	0.11736067	0.58328166	0.95688199	0.41225112

Table 7.2: Estimation output in the low stress regime for Germany. Standard errors reported in blue, p-values of the t-statistic reported in red.

Table 8 – Estimation output for Italy

Table 8.1 – High stress regime

High stress regime			Quarterly frequency		
Std Errors in blue & p-vlaues of the t-stat in red			Included observations: 26		
	Output growth (y)	Inflation (π)	GDP ratio (f)	ST Interest rate (i)	CLIFS (s)
Constant	1.566677124	1.600117311	3.784929066	0.009151689	0.092887099
	2.046158567	0.553363927	1.137749036	0.40805227	0.109583446
	0.45575409	0.01118312	0.00460019	0.98240239	0.4099614
Output growth (1)	0.233366447	0.076907724	-0.610365555	0.043502869	-0.010597639
	0.157613749	0.042625124	0.087639782	0.031431898	0.008441114
	0.15940483	0.09130168	0.00000454	0.18659581	0.22851119
Output growth (2)	0.44313365	-0.043801705	-0.966873234	0.003025713	-0.000406063
	0.214070966	0.057893436	0.119032337	0.042690799	0.01146472
	0.05612556	0.46101335	0.00000071	0.94443351	0.97221306
Inflation (1)	-0.483414293	0.089190107	-0.858539059	0.400058035	-0.042314604
	0.729926049	0.197401488	0.40586916	0.145564467	0.039091698
	0.5178396	0.65786258	0.05154707	0.01493654	0.2961496
Inflation (2)	-0.843999651	-0.010400723	-0.066397679	-0.22226742	0.01467203
	0.753153323	0.203683081	0.418784487	0.150196533	0.04033565
	0.28007074	0.9599489	0.87613943	0.15961008	0.7211218
GDP ratio (1)	0.115558594	0.081412969	-0.337854588	-0.004631355	-0.017941119
	0.341912608	0.09246698	0.190117592	0.068185437	0.018311368
	0.7400643	0.3925017	0.09583276	0.94674413	0.34273374
GDP ratio (2)	0.230385414	-0.171612249	0.047497213	0.033982976	0.017661538
	0.198250056	0.053614823	0.110235254	0.039535736	0.01061742
	0.26335412	0.00595365	0.67268938	0.40356515	0.11696924
ST interest rate (1)	0.830002628	-0.025226886	-0.191720313	1.119980262	0.02074989
	0.872480288	0.235953912	0.48513523	0.173993144	0.046726289
	0.35652324	0.91627368	0.69826614	0.0000112	0.66332909
ST interest rate (2)	-0.473665198	0.050807116	-0.401333222	-0.271757868	0.011104414
	0.746729466	0.20194581	0.415212557	0.148915464	0.039991616
	0.53542722	0.80477389	0.34908426	0.08799218	0.78505731
CLIFS (1)	-9.760344172	-0.574713748	4.586298125	-1.149078055	0.617143339
	4.715956267	1.275385067	2.622267297	0.940472889	0.25256632
	0.05616645	0.6587087	0.10072104	0.24063442	0.02738929
CLIFS (2)	0.889772835	0.227227277	4.99664766	0.203430632	-0.211982801
	4.407903828	1.192075244	2.450977364	0.879039968	0.236068358
	0.84273943	0.85138319	0.05951625	0.82011293	0.38338788

Table 8.1: Estimation output in the high stress regime for Italy. Standard errors reported in blue, p-values of the t-statistic reported in red.

Table 8.2 – Low stress regime

Low stress regime			Quarterly frequency		
Std Errors in blue & p-vlaues of the t-stat in red			Included observations: 68		
	Output growth (y)	Inflation (π)	GDP ratio (f)	ST Interest rate (i)	CLIFS (s)
Constant	-1.44512589	0.414213679	1.992037119	0.081708301	0.035717386
	0.84456206	0.322234636	0.834093105	0.152524347	0.018847836
	0.09250105	0.20383642	0.02026342	0.59424559	0.06316286
Output growth (1)	2.29516018	-0.102499598	-1.14614848	0.032154035	-0.009795518
	0.19814448	0.075600144	0.195688334	0.035784057	0.00442193
	0	0.18050639	0.00000025	0.37266853	0.03075648
Output growth (2)	-1.16270025	0.081277156	0.269667427	-0.041185623	0.006842096
	0.2723014	0.103894015	0.268926032	0.049176486	0.006076868
	0.00007485	0.4372713	0.32021621	0.40580594	0.26491568
Inflation (1)	1.29947756	0.338511648	-0.565602113	0.039486567	-0.00446364
	0.36664897	0.139891435	0.362104096	0.066215259	0.008182394
	0.0007943	0.01874015	0.1238264	0.55331156	0.58752609
Inflation (2)	-0.73296221	0.357048818	-0.255181949	-0.032342398	-0.004371189
	0.37238746	0.1420809	0.36777145	0.067251605	0.008310458
	0.05390663	0.01482338	0.4905881	0.63241685	0.60093815
GDP ratio (1)	0.39949129	-0.062675145	0.629389654	0.039563678	-0.003279638
	0.14191835	0.054147599	0.14015917	0.025629856	0.003167149
	0.00668666	0.25190087	0.00003513	0.1282059	0.30480071
GDP ratio (2)	-0.12020855	0.043066977	0.054078483	-0.05004137	0.002684499
	0.1532357	0.058465626	0.151336231	0.027673721	0.003419715
	0.43601352	0.46437427	0.72215702	0.07584182	0.43570029
ST interest rate (1)	-0.53577559	0.085680897	0.991049906	1.630218922	0.009351228
	0.70575524	0.269274212	0.697006899	0.127456421	0.015750126
	0.45088966	0.75150221	0.16051431	0	0.55504568
ST interest rate (2)	0.48184235	0.019228558	-0.635986939	-0.658370328	-0.004946574
	0.68807119	0.26252703	0.679542053	0.124262756	0.015355477
	0.48660118	0.94186829	0.35327039	0.00000196	0.74852712
CLIFS (1)	-13.3464518	3.573596013	2.291795119	-0.303901858	0.508730852
	6.45549796	2.463033969	6.375477448	1.165835721	0.144065397
	0.04324204	0.15229131	0.7205716	0.79528416	0.00082683
CLIFS (2)	16.3047028	-4.045580312	-4.412102709	-0.197459546	0.139184023
	7.53626183	2.875389162	7.442844473	1.361017119	0.168184478
	0.03470902	0.1648663	0.55566108	0.88515767	0.41136684

Table 8.2: Estimation output in the low stress regime for Italy. Standard errors reported in blue, p-values of the t-statistic reported in red.

Table 9 – Estimation output for the U.K.

Table 9.1 – High stress regime

High stress regime			Quarterly frequency		
Std Errors in blue & p-vlaues of the t-stat in red			Included observations: 27		
	Output growth (y)	Inflation (π)	GDP ratio (f)	ST Interest rate (i)	CLIFS (s)
Constant	-1.42407035	2.91542702	0.44496789	0.506624305	-0.13215066
	4.8432469	1.59028615	2.3249968	0.517489788	0.076463761
	0.77251347	0.08543405	0.85063212	0.34215016	0.10318449
Output growth (1)	0.39209253	0.00040361	-0.13765407	-0.041841643	0.012174219
	0.58744295	0.19288762	0.28200152	0.062766928	0.009274377
	0.5139931	0.99835634	0.63207803	0.51451391	0.20781143
Output growth (2)	-0.21125749	0.10938264	0.12150944	-0.048197639	0.009456746
	0.58249896	0.19126426	0.27962816	0.062238673	0.009196323
	0.72159445	0.57534205	0.66970034	0.44998696	0.31909586
Inflation (1)	0.28456263	0.18304138	-0.20748329	-0.022519643	0.012635718
	1.14143091	0.37479026	0.547943	0.121959267	0.018020576
	0.8062983	0.63190406	0.70991888	0.85582461	0.49326183
Inflation (2)	-1.33991247	0.56930707	0.79883523	-0.101721211	0.019899415
	1.53178667	0.50296406	0.73533297	0.163667882	0.024183399
	0.39465766	0.27435442	0.29341675	0.54301873	0.42268576
GDP ratio (1)	0.11679817	-0.08268302	1.08904358	-0.134048945	0.023247104
	1.00680626	0.33058609	0.48331654	0.107574932	0.015895162
	0.90908931	0.805685	0.03862589	0.23066578	0.162962
GDP ratio (2)	0.34838301	-0.08613438	-0.46873447	0.114840613	-0.01615614
	0.99331852	0.32615737	0.47684176	0.106133798	0.015682221
	0.73036879	0.79508318	0.34024029	0.29527526	0.31822953
ST interest rate (1)	-1.07204073	0.80401453	1.18367755	1.363478846	-0.048320391
	2.53077524	0.8309832	1.21489663	0.270407512	0.039955137
	0.67749591	0.3476699	0.34440716	0.00012018	0.24408946
ST interest rate (2)	2.60123549	-1.37321685	-1.97843218	-0.412420645	0.061147574
	2.63448765	0.8650373	1.26468369	0.281488944	0.041592518
	0.33815462	0.13197024	0.13729212	0.16225685	0.16090954
CLIFS (1)	-33.4085351	10.33245131	19.87684461	0.243526539	0.570445031
	17.17534645	5.63954638	8.24501134	1.835146253	0.271159332
	0.06954735	0.08560971	0.02830552	0.89608409	0.05157212
CLIFS (2)	12.69508799	-5.98967671	-3.76701685	-0.523212319	0.125785884
	15.86187004	5.20826477	7.61447804	1.694804321	0.250422552
	0.43523	0.26702994	0.62752363	0.76152132	0.62230263

Table 9.1: Estimation output in the high stress regime for the U.K. Standard errors reported in blue, p-values of the t-statistic reported in red.

Table 9.2 – Low stress regime

Low stress regime			Quarterly frequency		
Std Errors in blue & p-vlaues of the t-stat in red			Included observations: 67		
	Output growth (y)	Inflation (π)	GDP ratio (f)	ST Interest rate (i)	CLIFS (s)
Constant	1.210368585	1.259997556	-0.225553489	-0.220165626	0.092878084
	0.405496335	0.658443503	0.526288214	0.172942919	0.029025747
	0.00419937	0.06078796	0.66987727	0.20825862	0.00226539
Output growth (1)	1.2462176	-0.551100492	0.142448931	0.047588507	-0.016236021
	0.169913592	0.275905085	0.220528555	0.072467616	0.012162549
	0	0.0506459	0.5209544	0.51407217	0.18730459
Output growth (2)	-0.4603632	0.282582705	-0.430383144	-0.006578554	0.003305488
	0.151229282	0.245565569	0.196278442	0.064498816	0.010825111
	0.00355121	0.25472829	0.03249873	0.91912501	0.76122887
Inflation (1)	-0.047304147	0.389536349	0.170970492	-0.007128236	-0.018543195
	0.094450796	0.153368866	0.122586412	0.040282969	0.006760862
	0.61845103	0.01389162	0.16861628	0.8601829	0.00816763
Inflation (2)	-0.084067475	0.188928611	0.016580794	0.065253837	0.003335066
	0.084890082	0.137844213	0.110177691	0.036205355	0.006076499
	0.32628255	0.1759702	0.8809177	0.07687687	0.58529247
GDP ratio (1)	-0.092259907	0.088864243	0.650510368	0.006829775	0.002277059
	0.078404711	0.127313289	0.101760414	0.033439364	0.005612271
	0.24428737	0.48806759	0.00000003	0.83890365	0.68648809
GDP ratio (2)	0.070735916	-0.095574929	0.25350674	-0.000982584	-0.003759831
	0.067891902	0.110242628	0.088115982	0.028955684	0.004859756
	0.30193979	0.38966864	0.00567178	0.97305039	0.44238181
ST interest rate (1)	-0.149814819	-0.003906346	0.812869085	1.542134905	0.029434308
	0.270768077	0.439672238	0.351426228	0.115481738	0.019381792
	0.58226325	0.99294272	0.02441683	0	0.13447459
ST interest rate (2)	0.236214273	0.091044414	-0.791272934	-0.556532974	-0.025421183
	0.276092333	0.448317746	0.358336508	0.117752517	0.019762906
	0.39588566	0.83980852	0.03134269	0.00001582	0.20362841
CLIFS (1)	-1.923762425	0.908945577	5.60723924	0.079237604	0.5352663
	2.07931839	3.376389784	2.69871924	0.886822793	0.148839245
	0.35883751	0.78876031	0.04232999	0.92912256	0.00068321
CLIFS (2)	-6.629375196	-1.513254446	-0.560043408	0.576821771	0.065203217
	2.138369331	3.472276492	2.775360658	0.912007835	0.153066158
	0.00302497	0.66464963	0.8408112	0.52965089	0.67175483

Table 9.2: Estimation output in the low stress regime for the U.K. Standard errors reported in blue, p-values of the t-statistic reported in red.

Table 10 – Estimation output for France

Table 10.1 – High stress regime

High stress regime			Quarterly frequency		
Std Errors in blue & p-vlaues of the t-stat in red			Included observations: 30		
	Output growth (y)	Inflation (π)	GDP ratio (f)	ST Interest rate (i)	CLIFS (s)
Constant	0.852844427	0.952239125	0.097329215	0.289263497	0.143703241
	0.999255914	0.445425014	1.28014301	0.460602644	0.117630952
	0.40402546	0.04574346	0.94019014	0.53747288	0.23678354
Output growth (1)	0.346855164	0.159696115	-0.807404461	0.016991781	-0.009602483
	0.080702645	0.035973744	0.103387857	0.037199531	0.009500198
	0.0003882	0.00028146	0.00000024	0.65301244	0.32482786
Output growth (2)	0.502594604	-0.121508033	0.161993047	-0.017003479	0.007887363
	0.166507452	0.074221812	0.213312074	0.076750882	0.019601015
	0.00706685	0.11806719	0.45692189	0.82703474	0.69188404
Inflation (1)	0.876096218	1.023223798	-0.740163052	0.159418108	-0.082829763
	0.457968034	0.204142317	0.586701134	0.211098363	0.05391133
	0.07093929	0.00007735	0.2223736	0.45939838	0.14092463
Inflation (2)	-0.435789651	-0.391274045	1.138873227	-0.099724111	0.052146764
	0.545977332	0.243373051	0.699449516	0.251665864	0.064271657
	0.43462813	0.12438895	0.11994243	0.69633109	0.42721278
GDP ratio (1)	0.221336889	0.058395009	0.9319442	-0.031858947	-0.000576253
	0.154601246	0.06891454	0.198059077	0.071262768	0.018199434
	0.16848551	0.40734541	0.00015404	0.65988409	0.97507085
GDP ratio (2)	-0.011129329	-0.084538337	-0.12635138	0.022208953	0.002518101
	0.116700141	0.052019869	0.149504113	0.05379242	0.013737771
	0.92502206	0.12061069	0.40855158	0.68432807	0.85650636
ST interest rate (1)	-0.527554086	-0.043353813	-0.193445712	0.809552106	0.003289434
	0.525415875	0.234207644	0.67310831	0.24218815	0.061851192
	0.32796198	0.85510565	0.77692347	0.00342006	0.95814128
ST interest rate (2)	0.337937991	0.044079349	0.374421131	0.068619453	0.026708417
	0.487077909	0.217118239	0.623993686	0.224516433	0.057338103
	0.49619906	0.84127774	0.55556929	0.763208	0.64664995
CLIFS (1)	-9.497059906	-0.896870711	0.159088538	-3.480996622	0.424653605
	2.250333224	1.0031011	2.882893468	1.03728126	0.264905952
	0.00046337	0.38245577	0.95656832	0.00331945	0.12542135
CLIFS (2)	-0.411043779	-1.246425048	0.238970512	1.540500698	-0.412865233
	2.427004054	1.081853306	3.109225808	1.118716907	0.285703385
	0.86730157	0.26356264	0.93953967	0.18451359	0.16472617

Table 10.1: Estimation output in the high stress regime for France. Standard errors reported in blue, p-values of the t-statistic reported in red.

Table 10.2 – Low stress regime

Low stress regime			Quarterly frequency		
Std Errors in blue & p-vlaues of the t-stat in red			Included observations: 64		
	Output growth (y)	Inflation (π)	GDP ratio (f)	ST Interest rate (i)	CLIFS (s)
Constant	0.89930465	0.298593968	1.436151893	0.222431988	0.066154027
	0.76581187	0.23565288	0.755879656	0.15250333	0.034718909
	0.24551832	0.21066187	0.06288294	0.15059326	0.06215685
Output growth (1)	1.97397442	0.017440644	-0.875871221	0.102414642	-0.041530046
	0.23598157	0.0726154	0.232920997	0.046993232	0.010698479
	0	0.8111186	0.00042502	0.03377096	0.00028903
Output growth (2)	-1.08346437	-0.016732349	0.252472894	-0.125377741	0.03634643
	0.27578433	0.084863363	0.272207535	0.05491953	0.01250298
	0.00024876	0.84445018	0.35787093	0.02647259	0.00531696
Inflation (1)	-1.37301634	1.12706335	0.014328667	0.28552984	-0.047624956
	0.51768941	0.159301527	0.510975227	0.103092368	0.023470009
	0.01052623	0	0.97773413	0.00771837	0.04747516
Inflation (2)	0.9305787	-0.249408787	-0.375643933	-0.291137217	0.035706876
	0.49874499	0.153472018	0.492276505	0.099319787	0.022611143
	0.06760202	0.11007197	0.4488019	0.00497253	0.1202471
GDP ratio (1)	0.14855872	-0.04949027	0.552332608	-0.020649404	-0.002066525
	0.18034269	0.055494406	0.178003734	0.035913339	0.008176031
	0.41376873	0.37652774	0.00307063	0.56773866	0.80143598
GDP ratio (2)	-0.19627534	0.001198859	0.047206465	0.002944739	-0.00108995
	0.16638254	0.051198637	0.164224635	0.033133322	0.007543132
	0.24340236	0.98140651	0.7748883	0.92951589	0.88565717
ST interest rate (1)	0.18235129	0.2075494	0.569576418	1.198558223	0.052670182
	0.65699894	0.202169357	0.648477981	0.130834387	0.029785757
	0.78243617	0.30926617	0.3837303	0	0.08276583
ST interest rate (2)	0.04173774	-0.211067754	-0.447908213	-0.169799224	-0.048696429
	0.66451397	0.204481855	0.655895545	0.132330926	0.030126459
	0.95015455	0.30666214	0.49764709	0.20502535	0.11194527
CLIFS (1)	-11.77900346	-0.469908021	6.092533901	-0.815484627	0.60175147
	3.2534266	1.001132754	3.21123121	0.647885479	0.147497611
	0.00065778	0.64072597	0.06324794	0.21365983	0.00015243
CLIFS (2)	4.30706017	-0.616189821	-2.449035797	-1.198888096	-0.094673941
	3.8190342	1.175179495	3.76950315	0.760520247	0.173140042
	0.26448928	0.60223049	0.51869387	0.12088329	0.58680726

Table 10.2: Estimation output in the low stress regime for France. Standard errors reported in blue, p-values of the t-statistic reported in red.

Summary

Introduction

Economic downturns are often associated with periods of financial stress or even with financial crisis as in the Global Financial Crisis in 2008. During such periods, the effects of fiscal developments on economic activity might be different from what is usually observed in good or normal times, meaning that financial stress can act as a non-linear propagator of fiscal shocks on output growth. In financial stress periods the quality of financial institutions' assets deteriorates, as the share of nonperforming loans increases and negative sentiments in the markets depress the value of other financial assets.

In 2020, although the Covid-19 recession did not originate from financial markets, a quieter crisis has gained momentum in the financial sector triggering conditions of financial stress in most countries. For this reason, the present study aims to investigate whether and how non-linearities in the transmission of financial stress in the economic activity materialized also during the Covid-19 pandemic, and how the effects of fiscal policy shocks on economic activity differ in times of financial instability.

In this study contributes to the fiscally related vector autoregression (VAR) literature by estimating a Threshold Vector Autoregression (TVAR) model including a measure representing financial instability, namely the Country-Level Index of Financial Stress (CLIFS), developed by Duprey et al. (2015) for the ECB. I employ a quarterly dataset, for Germany, Italy, the U.K. and France for the period 1997:1-2021:1, encompassing macro, fiscal and financial variables. These are GDP growth (y), inflation (π), the fiscal variable (f), the short-term interest rate (i), and the indicator for financial market conditions (s), (i.e. the CLIFS).

Vector autoregressive models in macroeconomic and fiscal policy analysis: A literature review

In 1980s Sims' paper "Macroeconomics and Reality" revolutionized the study of systems driven by random impulses for the first time by introducing vector autoregression (VAR) models as an alternative to the traditional large-scale dynamic simultaneous equation models used in academic and policy work at the time. A VAR is an n-equation, n-variable linear model in which each variable is in turn explained by its own lagged values, plus current and past values of the remaining n-1 variables. This simple framework is able to explain the time dependence and the inter-dependence of the model's variables in a systematic way in order to capture rich dynamics in multivariate time series. As Sims (1980) and others argued, VARs provide a coherent and credible approach to data description, forecasting, structural inference and policy analysis. VARs come in three varieties: reduced form, recursive and structural. A reduced form VAR expresses each variable as a linear function of its own past values, the past values of all other variables being considered, and a serially uncorrelated error term. If the different variables are correlated with each other, as they typically are in macroeconomic applications, then the error terms in the reduced form model will also be correlated across equations. A recursive VAR constructs the error terms in each regression equation to be uncorrelated with the error in the preceding equations. A structural VAR uses economic theory to sort out the contemporaneous links among the variables. Structural VARs require "identifying assumptions" that allow correlations to be interpreted causally.

VAR models have become the most popular tool for investigating the effects of monetary policy during the nineties. However, these models are recently getting popular also from the research on the effects of fiscal policy, notably regarding the qualitative responses of macroeconomic aggregates to changes in government expenditures or revenues. In this context, the main difficulties come from the approaches used to identify the changes in fiscal policy, since both government expenditures and revenues, to some extent, automatically respond to fluctuations in economic activity and thus these fluctuations need to be distinguished from deliberate policy changes. It is possible to separate these effects using estimated elasticities of tax revenues and government expenditures on output developments or to use external information such as the expected contemporary effects of the fiscal variables.

Within the VAR framework, conventional VAR models are used to capture the linear dependence among multiple time series, but they might be unable to capture certain effects if these only materialize under particular circumstances. Indeed, non-linearity could be one of the reasons why these effects arise, and, for this reason, theoretical work in macroeconomics relies increasingly on specifying highly non-linear models. The corollary applies to theoretical models where higher-order approximations and global solutions are increasingly used in order to account for important dynamics which would be neglected in linear, first-order approximations.

For example, when studying differences in the characteristics of shocks, these can differ with regards to their direction (positive vs. negative shocks) as well as to their size (small vs. large shocks). Moreover, non-linearities can arise due to differences in initial conditions (regime-dependencies) that describe the point of the business cycle at which the economy is situated when a shock hits. If the system is characterized by non-linearity, one would then expect disproportionate effects as a response to shocks of different magnitudes. Equivalently, the direction of a shock will lead to asymmetric effects if non-linearity is present. Most importantly, these mechanisms can operate to a different extent depending on whether the economy is very vulnerable or not at the time when the shock hits. Thus, in contrast to linear models, initial conditions can lead to a heterogeneous propagation of shocks, in the sense that they serve as an amplification (or attenuation) mechanism of shocks.

One approach to capture non-linear dynamics in the DGP is the use of regime-switching models, such as the Threshold VAR and the Markow-switching VAR models. These models allow their parameters to take on different values in each of some fixed number of regimes, where, in general, the regime in operation at any point in time is unobserved by the econometrician. Application of regime-switching models are usually motivated by economic phenomena that appear to involve cycling between recurrent regimes. For example, regime-switching models have been used to investigate the cycling of the economy between business cycle phases (expansion and recession), "bull" and "bear" markets in equity returns, and high and low volatility regimes in asset prices.

A threshold VAR (TVAR) model is a non-linear multivariate system of equations that models non-linearity additively and can consequently be estimated by OLS. TVARs condition on the initial environment and approximate the non-linear DGP by several regime dependent DGPs which are by themselves linear. Each regime is defined by boundaries (equal to certain values of the threshold variable) and coefficients of the VAR system are specific to each regime. On the other hand, in Markov switching models time-variation of the parameters is governed by a discrete-valued latent stochastic process with limited memory. More specifically, the current value of the state indicator is determined only by the value of the state indicator from the previous period, thus the Markov property, and the transition matrix. The latter characterizes the properties of the Markov process by determining with what probability each of the states can be visited next period, given the state in the current period. Markov switching models presume a finite number of regimes and exogeneity of the Markov process which is defined as its independence of the model unpredictable innovations.

However, the assumption that the latent state is exogenous is quite unrealistic in a business cycle context where endogenous movements can be expected to lead to regime-switches. Models with endogenous switching like the TVAR, might thus be more appropriate to capture non-linear dynamics if, as often is the case, regimes are associated with recurring dichotomous, i.e. "good" and "bad", states of the economy. Unlike in TVAR models, in MSVARs, the state variable is generally not observed. As a result, MSVARs thus suffer from a lack of tractability of the underlying regime-switching process as the variable(s) which cause a regime-switch cannot be identified. In contrast, TVARs explicitly model the endogenous regime-switching process which is why they are also described as "self-exciting". TVARs can therefore be viewed as a type of MSVARs with endogenous switching where the probability structure is modelled simplistically. TVARs have the advantage that the regime-switching is tractable, but also require the choice of a threshold variable in order to endogenize the regime-switching. Since the focus of this work is on the effect on output growth to fiscal policy shocks for generating non-linearities, country level financial stress indicator is considered as (endogenous) switching variable. The latter was chosen as switching variable as it constitutes the channel through which non-linearities could materialize.

Nonlinear VAR models have been recently used in fiscal policy analysis, particularly after the Global Financial Crisis in 2008, where financial stress gained increased importance among macroeconomists at that time. The idea was that these models were the most adequate to capture possible nonlinearities such as asymmetric reactions to shocks of various macroeconomic variables depending on the different states of financial markets. Furthermore, the application of a nonlinear framework with regime switching was motivated by the lively debate on the ability of fiscal policy to shorten recessions and to facilitate a subsequent recovery of the economic activity.

The literature dealing with the effects of fiscal policy during the periods of financial stress is relatively scarce but growing. For example, Afonso et al. (2011) used a TVAR model to show that for the US, Germany, Italy and the UK, the responses of economic growth to a fiscal shock are mostly positive in both financial stress regimes; financial stress has a negative effect on output growth and worsens the fiscal position; the nonlinearity in the response of output growth to a fiscal shock is mainly associated with different behavior across regimes; the size of the fiscal multipliers is higher than average in the GFC.

Crafts and Mills (2013) estimate the government expenditure multiplier for interwar Britain (1919-1938) based on quarterly data. They find that the expenditure multiplier is less than one (between 0.3 and 0.8) depending on the model specification and the sample period. Rafiq (2014) finds larger government spending multipliers in recession than in expansion for UK data while using a small-scale Bayesian time-varying VAR model.

Methodology

The starting point of our analysis is a linear VAR model without exogenous variables, whose reduced form can be specified as:

$$Y_t = c + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \cdots + \Phi_p Y_{t-p} + \varepsilon_t \tag{1}$$

where Y_t is a (n x 1) vector of stationary endogenous variables included in the VAR (in our case n = 7), $Y_{t-1}, \dots, Y_{t-p}$ are (n x 1) vectors of the lagged values of the endogenous variables, c is a (n x 1) vector of constant terms, $\Phi_1, \dots, \Phi_p$ are (n x n) coefficient matrices, and ε_t is a (n x 1) vector of white noise disturbances with $E(\varepsilon_t) = 0$ and variance-covariance matrix $E(\varepsilon_t \varepsilon_t') = \sum_\varepsilon$. As the components of ε_t may be instantaneously correlated (i.e. the matrix $\sum_\varepsilon$ may not be diagonal), the impulse responses obtained from the reduced form model might not properly reflect the relationships between the variables. In order to consider a model with uncorrelated residuals, we can model the instantaneous relationships between variables directly by defining a structural VAR (SVAR) model in the A-B form[9]. Hence, I multiply both sides of equation (1) by the matrix A, which is a (n x n) matrix representing the structural contemporaneous relationships between the endogenous variables. If the reduced form disturbances are linear combinations of the structural shocks U_t in the form $\mathrm{A}\varepsilon_t = BU_t$, the SVAR model can be represented as:

$$\mathrm{A}Y_t = \bar{c} + \overline{\Phi}_1 Y_{t-1} + \overline{\Phi}_2 Y_{t-2} + \cdots + \overline{\Phi}_p Y_{t-p} + BU_t \tag{2}$$

where Y_t is again a (n x 1) vector of stationary endogenous variables at time t, A is again a (n x n) matrix representing the structural contemporaneous relationships between the endogenous variables, and B is a (n x n) matrix (often a diagonal matrix containing the errors' standard deviations). I further assume that both A and B are non-singular. $\bar{c} = \mathrm{A}c$ is a (n x 1) vector of constant terms, $\overline{\Phi}_1 = \mathrm{A}\Phi_1$, …, $\overline{\Phi}_p = \mathrm{A}\Phi_p$ are coefficient matrices of the p lagged values of all endogenous variables, and U_t is a (n x 1) vector containing the structural shocks with $E(U_t) = 0$ and variance-covariance matrix $E(U_t U_t') = \sum_U = \mathrm{I}_n$.

A SVAR model can be used to identify shocks and trace these out by employing impulse response analysis and forecast error variance decomposition through imposing restrictions on the matrices A and B. Incidentally, because a SVAR model is a structural model, it departs from a reduced form VAR(p) model and only restrictions for A and B can be added.

[9] A detailed description and derivation of the A-B model, as well as the corresponding A and B models can be found in Amisano and Giannini (1997), Lutkepohl (2005) and Lutkepohl and Kratzig (2004). Further applications of the A-B model can be found in Pagan (1995), Breitung and Lutkepohl (2004) and Blanchard and Perotti (2002).

A challenge for the benchmark VAR model is that it might not be able to capture possible non-linearities in the transmission of financial stress in the economic activity. Uncovering non-linearities in the data allows us to account for the potential shifts in the behaviour of economic variables depending on different financial stress regimes. For this reason, besides the benchmark VAR model, I define a threshold vector autoregressive (TVAR) model.

I follow the approach used by Afonso et al., (2011), Balke (2000) and Atanasova (2003) for the identification and estimation of a structural TVAR model containing 5 stationary endogenous variables, namely GDP growth (y), inflation (π), the fiscal variable (f), the short-term interest rate (i), and the indicator for financial market conditions (s), for which I have chosen the Country-Level Index of Financial Stress (CLIFS). Based on its linear version of equation (2), the TVAR model can be specified through the structural A-B form as10:

$$\mathrm{A}Y_t = \begin{cases} \bar{\Phi}^L(L)Y_{t-1} + BU_t & if\ I[s_{t-d}, \gamma] = 0 \\ (\bar{\Phi}^L(L) + \bar{\Phi}^H(L))Y_{t-1} + BU_t & if\ I[s_{t-d}, \gamma] = 1 \end{cases} \tag{3}$$

where $\mathrm{A} = (\mathrm{I} - \bar{\Gamma}^L)$ when $I[.] = 0$ and $\mathrm{A} = (\mathrm{I} - \bar{\Gamma}^L - \bar{\Gamma}^H)$ when $I[.] = 1$. Assuming $B = \mathrm{I}$, the model can therefore be rewritten as:

$$Y_t = \begin{cases} \bar{\Gamma}^L Y_t + \bar{\Phi}^L(L)Y_{t-1} + U_t & if\ I[s_{t-d}, \gamma] = 0 \\ (\bar{\Gamma}^L + \bar{\Gamma}^H)Y_t + (\bar{\Phi}^L(L) + \bar{\Phi}^H(L))Y_{t-1} + U_t & if\ I[s_{t-d}, \gamma] = 1 \end{cases} \tag{4}$$

or in the compact form:

$$Y_t = \bar{\Gamma}^L Y_t + \bar{\Phi}^L(L)Y_{t-1} + \left(\bar{\Gamma}^H Y_t + \bar{\Phi}^H(L)Y_{t-1}\right)I[s_{t-d}, \gamma] + U_t \tag{5}$$

where Y_t is a (n x 1) vector of stationary endogenous variables; $\bar{\Gamma}^L$ and $\bar{\Gamma}^H$ are (n x n) matrices representing the structural contemporaneous relationships between the endogenous variables in the low-stress and high-stress regime respectively. I assume that $\bar{\Gamma}^L$ and $\bar{\Gamma}^H$ have a recursive structure. $\bar{\Phi}^L(L) = \mathrm{A}\sum_{i=1}^{p} \Phi_i^L L^{i-1}$ and $\bar{\Phi}^H(L) = \mathrm{A}\sum_{i=1}^{p} \Phi_i^H L^{i-1}$ are (structural) lag polynomial matrices in the low-stress and high-stress regime respectively; U_t is again a (n x 1) vector of structural shocks, which are assumed to be white noise, uncorrelated and homoscedastic, with variance–covariance matrix typically normalized such that: $E(U_t) = 0$ and $E(U_t U_t') \equiv \sum_U = \mathrm{I}_n$. This means, first, that there are as many structural shocks as variables in the model. Second, structural shocks by definition are mutually uncorrelated, which implies that $\sum_U$ is diagonal. Third, I normalize the

[10] Constants or other deterministic regressors have been suppressed for notational convenience.

variance of all structural shocks to unity. The latter normalization does not involve a loss of generality, as long as the diagonal elements of the matrix A remain unrestricted. s_{t-d} is the threshold variable that determines the dynamics of Y_t in different regimes, with a possible lag d; γ is the threshold value at which the regime switching occurs; $I[.]$ is an indicator function that governs the regime switches and that takes the value of 1 if, the threshold variable s_{t-d} is higher than the threshold value γ (high-stress regime), and 0 otherwise (low-stress regime).

Before starting with the estimation of a linear vs. a non-linear VAR model, I need to test if the system is indeed non-linear. First, I determine the threshold value over all possible values of the threshold variable, and second, I run a nonlinearity test for a threshold VAR model against a linear VAR model to see whether the threshold value is statistically significant. To do so, I follow the procedure introduced by Hansen (1996).

In order to allow estimation of the structural TVAR model of equation (5), we first need to derive its reduced-form representation because consistent estimation of the coefficients of the structural VAR model is not feasible. This involves expressing Y_t as a function of lagged Y_t only. To derive the reduced-form representation, I pre-multiply both sides of equation (5) by A^{-1}. Hence, the reduced-form TVAR is described as:

$$Y_t = c^L + \Phi^L(L)Y_{t-1} + (c^H + \Phi^H(L)Y_{t-1})I[s_{t-d}, \gamma] + \varepsilon_t \tag{7}$$

where again Y_t denotes the (n x 1) vector of the stationary endogenous variables, $c^L = \mathrm{A}^{-1}\bar{c}^L$ and $c^H = \mathrm{A}^{-1}\bar{c}^H$ are (n x 1) vectors of intercept terms in the low-stress and high-stress regime respectively, $\Phi^L(L) = \mathrm{A}^{-1}\bar{\Phi}^L(L)$ and $\Phi^H(L) = \mathrm{A}^{-1}\bar{\Phi}^H(L)$ are the (reduced-form) lag polynomial matrices in the low-stress and high-stress regime respectively, and $\varepsilon_t = \mathrm{A}^{-1}BU_t$ is the vector of reduced-form error terms. The reduced-form disturbances are then linear combinations of the structural form errors.

If the hypothesis of linearity (i.e. $H_0: \bar{\Gamma}^H = \bar{\Phi}^H(L) = 0$) is rejected by the data, I can proceed with the estimation of the Threshold VAR. Given the linearity of the model within each regime, the parameters can be recovered by least squares (LS). However, once estimated, the state dependent dynamics of TVARs allows for non-linear and asymmetric impulse-response functions. Note that the TVAR model is linear within each regime, but the changes in the parameters across regimes account for non-linearities.

For the purpose of this work, I use a recursive identification scheme, namely I rely on a Cholesky decomposition of the variance-covariance matrix of residuals $\sum_{\varepsilon}$ in each regime to recover the elements of A^{-1} and B. A possible solution for these elements is found solving the following equation:

$$\sum_{\varepsilon} = PP' \tag{9}$$

where the matrix $P = \mathrm{A}^{-1}B$ is known as the Cholesky decomposition of $\sum_{\varepsilon}$. Once the elements of A^{-1} and B have recovered, the impact of the different structural shocks can be evaluated. The recursive identification scheme implies that the matrix A^{-1} has a lower-triangular form, whereas the matrix B is diagonal. These particular forms of A^{-1} and B satisfy the required number of restrictions, thereby it will be possible to estimate the structural shocks U_t from the reduced form VAR residuals ε_t. Instead of deducing causal relationships from the data itself, the recursive identification scheme implies a certain causal ordering on the matrix Y_t, so that the disturbance to the first variable is predetermined relative to the disturbances to the variables following in the order. For this reason, the recursive structure embodied in A^{-1} and B needs economic justification, because the order of equations variables matters. In our model, the five variables are thus order as follows: GDP growth (y), inflation (π), the fiscal variable (f), the short-term interest rate (i), and the Country-Level Index of Financial Stress (s).

I order the $CLIFS$ last which implies that the $CLIFS$ reacts contemporaneously to all variables in the system. I assume that all new changes in both macroeconomic aggregates and economic policy that occur during one quarter are transmitted to financial markets within this quarter. The ordering of the fiscal variable after output is motivated by the need to identify the effects of automatic stabilizers in the economy. Hence, following Blanchard and Perotti (2002), I assume that all reactions of fiscal policy within each quarter (e.g. changes in government debt) are purely automatic because of implementation lags of fiscal policy measures. The interest rate shows up after the fiscal variable since the short-term interest rate can react contemporaneously to fiscal policy, but not vice versa. Moreover, the short-term interest rate does not have a contemporaneous impact on output growth or the inflation rate but can have an immediate impact on the $CLIFS$.

In VAR models, the interaction between economic variables is studied by considering the effects of changes in one variable on the other variables of interest. This kind of analysis is known as impulse response analysis. Impulse responses trace out the response of current and future values of each of the variables to a one-unit increase in the current value of one of the VAR errors, assuming that this error returns to zero in subsequent periods and that all other errors are equal to zero. For linear VAR models the impulse response functions are indeed linear and of less complexity than nonlinear IRFs. The linear structural impulse response functions can be defined as the change in the conditional expectation of the vector Y_{t+l} as a result of the shock U_{jt}:

$$IRF_y(l, \delta_{jt}) = E(Y_{t+l} | U_{jt} = \delta_{jt}) - E(Y_{t+l} | U_{jt}^0 = \delta_{jt}^0) \tag{15}$$

where Y_{t+l} is a vector of variables at horizon l, $U_{jt} = \delta_{jt}$ denotes the shock to the j-th equation that the expectations are conditioned on, and $U_{jt}^0 = \delta_{jt}^0$ denotes stochastic disturbance to the j-th equation at time 0 that would occur under the no shock scenario.

In non-linear VAR models, the computation of impulse responses is considerably more complicated than in linear VARs. In the linear case, the impulse responses can be derived directly from the estimated coefficients and the estimated responses are symmetric both in terms of the sign and of the size of the structural shocks. Furthermore, these impulse responses are constant over time as the covariance structure does not change. For this reason, linear VARs are said to be history-independent because no shocks hit the economy in intermediate periods.

However, these convenient properties do not hold within the class of nonlinear models as shown by Potter (1994) and Koop et al. (1996). In nonlinear models, the moving average representation is nonlinear in the structural disturbances U_t, because some shocks may lead to switches between regimes, and thus their Wold representation does not exist. This implies that, in contrast to linear models, we cannot construct the impulse responses as the paths the variables follow after an initial shock, assuming that no other shock hits the system. To cope with these issues, the analysis requires the computation of generalized impulse response functions (GIRFs), as developed by Koop et al. (1996), defined as the difference between the forecasted paths of variables with and without a shock to a variable of interest. The advantage of GIRFs is that not only it allows for the analysis of regime-dependent responses, but also that effects of shocks of different sizes and directions can be analyzed. Due to this history- and shock-dependence, GIRFs lend themselves as an appropriate framework to analyze the above-mentioned dimensions of non-linearity such as regime-dependencies, asymmetries (positive vs. negative shocks) and shock non-linearity (small vs. large shocks). The generalized impulse response functions (GIRFs) are computed following Koop, Pesaran and Potter (1996), and they are designed to trace out the effects of orthogonal structural shocks as in Kilian and Vigfusson (2011). Formally, the GIRFs are defined as:

$$GIRF_y(l, \delta_{jt}, \Omega_{t-1}) = E(Y_{t+l} | U_{jt} = \delta_{jt}, \Omega_{t-1}) - E(Y_{t+l} | U_{jt}^0 = \delta_{jt}^0, \Omega_{t-1}) \tag{16}$$

where again Y_{t+l} is a vector of variables at horizon l, Ω_{t-1} is the information set available before the time of shock U_{jt}. $U_{jt} = \delta_{jt}$ denotes the shock to the j-th equation that the expectations are conditioned on, and $U_{jt}^0 = \delta_{jt}^0$ denotes stochastic disturbance at time 0 that would occur under the no shock scenario. This implies that there is no restriction regarding the symmetry of the shocks in terms of their sizes because the effects of a U_{jt} shock depend on the magnitude of the current and subsequent shocks. Moreover, in the high-stress regime, the size of the fiscal shock matters, since a small shock is less likely to induce a change in the regime. Likewise, the impulse responses depend also on the entire history of the variables that affect the persistence of the different regimes.

The second part of dynamic analysis is performed by means of forecast error decompositions, which "decomposes" the variance of the forecast error into the contributions from specific shocks at a given horizon. The FEVD thus indicates which shocks contribute towards the fluctuations of each variable in the system. Because of that, FEVD is generally used in dynamic analysis to (1) to demonstrate how important a shock is in explaining the variations of the variables in the model, and (2) to show how that importance changes over time.

The computation and analysis of forecast error variance decomposition (FEVD) in linear models assumes that impulse responses and variance decomposition are not state dependent nor shock and composition dependent as it happens in the non-linear models. Based on the definition of linear impulse response function of equation (15), the corresponding FEVD for horizon h equals:

$$FEVD_{ij}(h) = \frac{\sum_{l=0}^{h} IRF_y\left(l, \delta_{jt}\right)^2}{\sum_{j=1}^{k}\sum_{l=0}^{h} IRF_y\left(l, \delta_{jt}\right)^2} = \frac{\sum_{l=0}^{h} IRF_y\left(l, \delta_{jt}\right)^2}{\sigma_i(h)} \quad i, j = 1, \dots, k \qquad (17)$$

where j and i refer to the j-th shock and i-th variable in Y_t respectively, $IRF_y\left(l, \delta_{jt}\right)$ are the linear impulse response functions computed in subsection 3.6 and h is the horizon. $\sum_{j=1}^{k} FEVD_{ij}(h) = 1$ for a given $i, l = 1, \dots, h$ and $\sigma_i(h)$ denotes the h-step forecast error variance of the i-th variable. Therefore, in linear VARs, $FEVD_{ij}(h)$ measures the relative contribution of a shock to the j-th equation in relation to the total impact of all k shocks on the i-th variable in Y_t after h periods, and these contributions sum to unity.

To allow for the analysis of regime-dependency of variance decompositions, I follow the approach of Lanne and Nyberg (2016), who propose a generalized version of the forecast error variance decomposition for multivariate nonlinear models. The computation of the state-dependent Generalized Forecast Error Variance Decomposition (GFEVD) for our TVAR model is similar to the one proposed in Lanne and Nyberg (2016). The innovations are: i) it is designed to simulate the importance of an orthogonal structural shock, and ii) it considers a one standard deviation shock in each variable. In particular, conditional on a specific history Ω_{t-1} and a forecast horizon of interest h, the $GFEVD_{ij}$ that refers to a variable i and a shock j whose size is δ_{jt} is given by:

$$GFEVD_{ij}(h, \Omega_{t-1}) = \frac{\sum_{l=1}^{h} GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)^2}{\sum_{j=1}^{k}\sum_{l=1}^{h} GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)^2} \quad i, j = 1, \dots, k \tag{18}$$

where h is an indicator that keeps track of the forecast errors, and k denotes the number of shocks to the i-th variable in the vector Y_t. Ω_{t-1} is the information set available before the time of shock δ_{jt}. Differently from Lanne and Nyberg (2016), in our case the object $GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)$ are the generalized impulse response functions à la Koop, Pesaran, and Potter (1996) computed in subsection 3.7 by considering an orthogonal shock as in Kilian and Vigfusson (2011)11. In our application we are interested in the contribution of an identified fiscal shock to the GFEVD of output growth and financial stress variable. In the above equation, the denominator measures the aggregate cumulative effect of all the shocks, while the numerator is the cumulative effect of the j-th shock. By construction, $GFEVD_{ij}(h, \Omega_{t-1})$ lies between 0 and 1 and for non-linear VARs it measures the relative contribution of a shock to the j-th equation in relation to the total impact of all k shocks on the i-th variable in Y_t after h periods, and these contributions sum to unity.

Variables and data

The TVAR model is estimated using quarterly data for the UK, Germany, Italy and France for the period 1997:1-2021:1. The TVAR of equation (4) consists of a five-dimensional system of endogenous variables $Y_t = \{y_t, \pi_t, f_t, i_t, s_t\}$, namely GDP growth ($y$), inflation ($\pi$), the fiscal variable ($f$), the short-term interest rate (i), and the Country-level index of financial stress (s).

Before estimating the model, I perform a battery of tests to check for the adequacy of the model. First, I check for the stability of our model by computing the roots of the characteristic polynomial, i.e. I employ the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test. For all five variables, both tests include a constant but no trend. Although some variables exhibit evidence of nonstationary behavior (cfr. Table 4 in appendix IV) and the Trace and Maximum Eigenvalue tests

[11] The object $GIRF_{y_i}\left(l, \delta_{jt}, \Omega_{t-1}\right)$ in Lanne and Nyberg's (2016) expression, refers to the GIRFs à la Pesaran and Shin (1998). This definition of the GIRF refers to a non-orthogonalized shock and it can be applied both to linear and nonlinear VAR models. Details can be found in Pesaran and Shin (1998) and Lanne and Nyberg (2016).

find evidence of cointegration (cfr. Table 5 in appendix IV), the model is specified without imposing cointegrating relationships. This choice is dictated by the fact that there is uncertainty about the number of cointegrating relationships as Table 5 shows that the order of integration changes when the tests are performed on a VAR including the integrated variables only rather than the entire set of variables. Hence, I avoid possible misspecification errors due to imposing long-run relationships not supported by theoretical underpinnings. There is an issue of whether the variables in a VAR need to be stationary. Sims (1980) and Sims, Stock, and Watson (1990) argued that the goal of a VAR analysis is to determine the interrelationships among the variables, not to determine the parameter estimates. Similarly, it is argued that the data need not be detrended. In a VAR, a trending variable will be well approximated by a unit root plus drift. However, the majority view is that the form of the variables in the VAR should mimic the true data-generating process. This is particularly true if the aim is to estimate a structural model as in our case.

I determine the optimal lag length (p) by minimizing the Schwarz information criterion, which attaches a larger penalty to the number of coefficients estimated in the model, hence I use only one lag given the low number of observations in the high stress regime (cfr. Table 6 in appendix IV). The main reason is that within the high financial stress regimes the number of observations is too low to allow estimating a TVAR model with five variables and the conventionally used four lags. The optimal value of the time delay (d) is chosen in such a way that it provides the minimum residuals variance. Therefore, the time delay of the threshold variable is set to 1.

In this chapter the developments of the model's variables are provided for Germany, Italy, the U.K. and France in the period 1997:1-2021:1. The data are provided by the International Financial Statistics (IFS) database of the International Monetary Fund (IMF).

A relevant issue with VARs used for fiscal policy analysis is the choice of the variables that describe fiscal developments. I preferred to work with a parsimonious VAR structure to describe fiscal policy in the most aggregated form. Therefore, I used the government debt-to-GDP ratio because it reflects the developments both in government revenue and expenditure. Moreover, the government debt ratio captures also government actions that may not be fully reflected in the fiscal balance (e.g. purchase of financial assets, recapitalization of banking sector, the calling of previously issued government guarantees or any stock-flow adjustments) and has thus, in principle, a wider coverage of government actions than the fiscal balance. In addition, usually government debt is not a policy variable, with governments focusing more in the short run on the budget deficit rather than on government debt when forming their policies (e.g. governments typically announce budget deficit paths as their target). The changes in the government debt ratio have an impact on the corporate sector expectations, consumption sentiment of households and on financial market conditions since it provides information about not only the current fiscal policy but also about past fiscal developments. In addition, the government debt ratio has a closer link to financial markets than the fiscal balance because it partly captures also the risk related to the refinancing of the outstanding stock of government debt, while influencing interest rates.

I also take a particular look at the Country-Level Index of Financial Stress (CLIFS) developed by Duprey et al. (2015). The $CLIFS$ is able to identify systemic financial stress episodes for each Eurozone country, including also the UK in a transparent, reproducible and objective way. Systemic financial stress episodes are defined as periods of financial stress associated with a substantial and prolonged negative impact on the real economy, or, alternatively, as real economic stress periods which are not ordinary recessions but are also associated with high financial stress. In their paper, Duprey et al. (2015), specify that no assumptions are made about the sequence of events, i.e. whether the financial market or real economic stress occurs first. Instead, the focus of their analysis is on the detection of periods in which financial market and real economic stress mutually reinforce each other. As a result, the $CLIFS$ is able to detect the high financial stress periods associated with the recent Covid-19 recession and for this reason, it is the best leading indicator of systemic financial stress that serves our purposes. In particular, I am allowed to study the effects of fiscal policy shocks on economic activity depending on financial market conditions considering also the impact of the pandemic, which is an issue not investigated so far in macroeconomic literature.

The $CLIFS$ contains data capturing three financial market segments: Equity market stress, bond market stress and foreign exchange market stress.

Results

I tested whether the data indicate the presence of a statistically significant threshold γ as defined by the values of the Country-Level Index of Financial Stress, and whether the optimal threshold values are reasonable in terms of identifying high and low stress periods that will be related to output fluctuations. Because the observed persistence of the $CLIFS$ is very low, when comparing to fluctuations of other macroeconomic variables, reasonable values of the threshold would have led to a segmentation of periods with high financial stress. Therefore, in order to avoid the presence of an implausible number of regime switches over time, I have determined the threshold from the $CLIFS$ smoothed by a 3-period moving average following Hansen’s (1996) procedure.

The tests for all countries reject the null hypothesis of linearity in the relationships between the times series. Since threshold effects appear to be present, a linear VAR reflecting a single regime may not be the most adequate specification to describe the dynamic behavior of the DGP. For this reason, I proceeded with the estimation of the TVAR model.

The threshold splits the sample into a high stress regime with more than one fourth of observations (from 29 for the case of Italy to 33 for the case of France) and a low stress regime with the remaining portion. Such division seems to be well in line with the fact that the duration of expansions is higher than the duration of recessions. Furthermore, the high stress periods identified using the estimated thresholds are more frequent than recessions. However, all recessions in all countries broadly have their counterpart among the high financial stress periods. Additionally, the average annual output growth rates are lower in high stress periods than in low stress periods.

The model's output for both the high stress regime and low stress regime as estimated by the TVAR model for Germany, Italy, U.K. and France respectively is provided. This shows that the coefficients of the high stress regime and the low stress regime differ noticeably in both sign and size, providing indication of the existence of separate economic dynamics during the different financial regimes.

The empirical results and the implications of our model are the following. First, the differences among the fiscal multipliers of various sizes and signs of shocks are large in the Euro area countries (i.e. Germany, Italy and France) and small in the U.K. Moreover, the initial state of the economy matters and both multipliers and the estimated responses to fiscal shocks differ substantially across regimes. In particular, in Germany and the U.K., differences in the estimated fiscal multipliers in the two regimes indicate that fiscal policy has larger effects on output growth in the high stress regime than in the low stress regime. The opposite is true for Italy and France, where the impact of fiscal policy in the low stress regime is much higher leading the economy to a switch to the high stress regime.

Specifically, for Germany cumulative multipliers range between 1.60-1.78 in the high stress regime with large differences between signs and sizes of shock within both regimes. Moreover, the response of output growth to fiscal shocks is faster in high stress regime in comparison to the low stress regime. The U.K. has the lowest effects of a fiscal shock on output growth in the high stress regime, with the cumulative multiplier over three years being between -0.92 and -0.94. However, if the fiscal shocks occur in the low financial stress regime, the cumulative multipliers are around 0.26-0.28. The cumulative fiscal multipliers in Italy after three years are about -0.31 and -0.42 in the high stress regime. Interestingly, in the low stress regime those multipliers are much higher with a size that ranges between 4.52 and 6.12, and therefore impulse responses have an explosive behavior. Such behavior leads the economy to switch to the high stress regime and when it happens so, the economy becomes less explosive and corrects the out of equilibrium conditions of the low stress regime. Similarly, in France the cumulative fiscal multiplier is 0.11 in the high stress regime and it is much higher (1.55-1.87) when the economy is initially in the low stress regime, implying a strong rapidity to switch to the high stress regime.

Second, fiscal policy shocks immediately decrease financial stress in all countries when the shock hits in both regimes, except in Italy (in the high stress regime), where fiscal shocks slightly increase financial stress. In the high stress regime for all countries, I do not document any sharp increase in financial stress except for Germany in the long term, when financial stress starts to explode. Interestingly, in the U.K. a positive fiscal shock in the high stress regime reflects efforts to reduce financial stress, rather than to stabilize economic growth. Indeed, output growth drops significantly and so does financial stress. In the low stress regime, the response of financial stress is negative in all countries immediately when the shock hits the economy. After few quarters these responses increase. However, the increase of financial stress is higher in Italy and France after 17 quarters, mainly when focusing on the low stress regime. Interestingly, those responses for the latter two countries dramatically decrease in the long-term indicating a reduction in financial stress. A detailed investigation of simulated impulse responses reveals that this result is mainly driven by the period of the Covid-19 pandemic characterized by a huge rising debt ratio in those countries.

Third, in Germany and in the U.K. fiscal shocks play a more important role when the economy is in the high stress regime because they contribute more to the variation of output growth. Furthermore, fiscal shocks are more important than shocks to the other variables in both regimes for the same reason. However, the relative contribution of fiscal shocks on output growth remains broadly constant over time with some little exceptions.

Therefore, I have found evidence of nonlinearities in the effects of a fiscal shock depending on the initial conditions, determined by the existence of financial stress. In addition, both the multipliers and the nature of these nonlinearities vary across countries and evolve over time. Finally, the estimated thresholds also match economic recessions, and the effectiveness of fiscal policy in the context of different financial stress regimes also differs across country, naturally something to bear in mind by policy makers.