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Risk, Asset Pricing and Monetary Policy transmission in Europe: Evidence from a Threshold-VAR approach

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Risk, Asset Pricing and Monetary Policy Transmission in Europe: Evidence from a Threshold-VAR approach

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Abstract

This paper investigates in how far monetary policy shocks impact European asset markets, conditional on different risk states. It focuses on four different asset classes: equity of industrial firms, equity of banks, high-grade corporate bonds, and high-yielding corporate bonds. We distinguish between macroeconomic risk, political risk, and financial risk. In a first step, we separately extract three factors via principal component analysis from a set of candidate variables that are assumed to be driven by these latent types of risk. Next, these factors augment a threshold-VAR model that contains assets and a short-rate. Our model is estimated with Bayesian techniques and identified recursively. We illustrate that during periods of severe crisis, different risk regimes coincide. This impedes a clear delimitation among these three types of risk. Further on, impulse responses show that we indeed see state-dependency in the reaction of asset prices to monetary policy shocks. AA-rated corporate bond yields only show minor state-dependency if we distinguish between states of high and macroeconomic or financial risk, but show very pronounced state-dependency for political risk. Their sensitivity to monetary policy shocks is highest if political risk is . Non-investment-grade corporate bond yields as well as equity of industrial firms face the strongest state-dependency when we differentiate between macroeconomic or financial risk. If these risks are high, junk bond yields are very sensitive to monetary policy shocks while the opposite holds for equity of industrial corporations. Surprisingly, financial equity in general reacts positively or insignificant to hikes in short-rates. The

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positive reaction is most pronounced for states of high financial risk.
As a consequence, monetary policy transmission via distinct asset markets highly depends on the degree of these different kinds of risk inherent in European asset markets. This also has strong implications for investors: they have to be aware of this varying degree of sensitivity of asset prices to changes in policy rates as they highly depend on the respective prevailing risk-regime.
Keywords: state-dependency, asset pricing, monetary policy

JEL classification: E44, G12, C11

1 Introduction

"Given this amount of policy and macroeconomic risk that there is around, there is no room for complacency for market participants so they have to be prepared for possible market adjustments. They cannot work under the assumptions that the current, very benign market environment is going to stay forever."[1]
The statement above emphasizes that the euro area is subject to different kinds of elevated risks. Albeit we have weathered major crises, namely the Financial Crisis and European Sovereign Debt Crisis, there is a lot of macroeconomic, political, and financial risk lurking around in Europe. Markets in general, but asset markets in particular, face these risks as they are highly relevant for asset pricing and the mechanisms that found them. Conditional on the degree of risk inherent in Europe, some assets might have a higher susceptibility to changes in monetary policy than others.

There are claims that complacency of markets was one harbinger of the Financial Crisis. For instance, the convergence of government bond yields before the Financial Crisis did not reflect differences in fiscal soundness of national budgets in Europe anymore. Foling the macroeconomic consequences of the Financial Crisis and the European Sovereign Debt Crisis, fiscal measures (re-)gained markets' attention. This resulted in peaks in e.g. political risk. Asset markets seem to face periods in which they are complacent or hysteric. This binary state of markets is linked to the (perceived) risk of investors. Hence, we want to examine the existence of asymmetric reactions of various asset prices to an unexpected hike in short-rates, conditional on distinct kinds of risk inherent in Europe. Does their reaction show state-dependency? And what implications result from potential asymmetries for monetary policy makers when we are in different regimes of risk? What is risk at all and what kind of risks, that are common to all assets, do exist in the euro area? How can they be subject to measurement and evaluation? However, given that the term risk is not precisely defined, answering these questions is not straight forward. Aggravating, there exits much overlapping to uncertainty. These issues hinder a strict delimitation of the phenomenon risk.

In addition, thinking about the fast field of risk from an economist's perspective, requires to distinguish between *systemic* and *systematic* kinds of risk as e.g. outlined

[1] Benoît Cœuré, Member of the Executive Board of the ECB (2017), interview conducted by Balasz Koranyi and Francesco Canepa for Reuters, on 17 May, 2017, and published on 18 May, 2017.

by Hansen (2012). Systematic risk cannot be eliminated via additional diversification, thus it requires an additional compensation for bearing it, for instance, a risk premium. It is a phenomenon subject to almost all assets, of course to a varying degree. On the contrary, systemic risk is a vague concept that, especially these days, primarily aims at potentially overheating or crumbling financial markets as well as possible self-enhancing, vicious feedback loops between financial markets and the real economy. Although we will take into account various financial variables within this paper, we will not deal with the latter type of risk but rather focus on macroeconomic and (economic) policy risk, supplemented with risk that stems from different aspects of financial market stress.

We want to answer the questions that arose before. First, we quantify the degree of macroeconomic, (economic) policy, and financial risk to study different risk regimes that arose in the euro area, respectively. We extract these risks from a set of variables via principal component analysis. The resulting distinction between high- and -risk regimes fits into the literature on state-dependent effects of monetary policy. Thus, these different risk regimes are an alternative way to drive state-dependence, especially of asset prices. We then analyze the sensitivity of equity and corporate bond yields to monetary policy shocks, conditional on high or risk inherent in European markets, respectively. Our paper fits into several strands of the existing literature. The general idea to incorporate factors into vectorautoregressions is prominently promoted by e.g. Bernanke et al. (2005). The authors also use a few factors extracted from a large set of macroeconomic indicators within an otherwise standard VAR-model. With this approach, they quantify the impact of a monetary policy tightening to macroeconomic variables. We fol Alessandri and Mumtaz (2019) and make use of state-dependent sensitivity of variables to monetary policy shocks. They investigate, in how far the reaction of macroeconomic series is state-dependent, conditional on high or financial risk, respectively. In addition, they augment their model with (forecast) uncertainty via an alternating covariance matrix within their threshold-VAR (TVAR)-model. Tenreyro and Thwaites (2016) show that during a bad state of the business cycle, i.e. when macroeconomic risk is elevated, the ability of monetary policy shocks to affect macroeconomic variables is hampered. Uncertainty about fiscal policy, interpretable as risk about economic policy, decreases real activity, as outlined in Fernández-Villaverde et al. (2015). This finding is even more pronounced during periods characterized by very interest rates. Estimating time-variant risk premia from a large data set of US equity is the aim in Gagliardini et al. (2016). Although the authors do not differentiate across different types of risk, they have a quite important finding: the time-varying risk premia deviate to a large extend from the standard time-invariant counterparts in crisis periods. This indicates regime-dependent non-linearities an issue we will address later.

All these paper have in common that they emphasize the need to take non-linearities into account. We want to point out the distinction among these three types of risk in our paper, but we believe that they rather interact, at least to some extent. Furthermore, we want to focus on asset markets instead of real activity because most of them have undoubtedly faced a strong boost in recent years. This boost, whom many assign to the extra-ordinary loose monetary policy, might go in hand with lurking risk. Thus, asset prices are possibly susceptible to adjustments in the monetary policy stance or unexpected hikes in short-rates, as outlined by Benoît Cœré.

Regressing risk related measures on financial variables or evaluating the impact of unexpected changes within vectorautoregressions is common practice to quantify the tense relationship between asset prices and risk. Beirne (2012) show in how far the EONIA is driven by liquidity needs and credit factors, both in normal times and periods characterized by unconventional monetary policy and the altered allotment procedures that accompany it. Aastveit et al. (2017) quantify the effects of monetary policy shocks on the US economy, conditional on high or uncertainty. They differentiate between three uncertainty classes: macroeconomic uncertainty, measured by the macroeconomic uncertainty factor of Jurado et al. (2015), economic policy uncertainty, using the EPU index of Baker et al. (2016), and (implied) financial market volatility. The key finding for this paper is that the transmission of short-(shadow)-rate changes is much weaker when uncertainty is high.[2]
An alternative to the usage of (threshold-indicated) risk regimes to obtain a distinction between periods is used by Jansen and Tsai (2010) or Chen (2007). Both papers investigate in how far the reaction of (US) asset prices to monetary policy differs when the respective asset markets are in bear or bull stages. Beside methodological differences, both paper find that monetary policy has a larger impact on assets when they are in bear markets.

Note that the above mentioned papers all have in common that they narrowly focus on one specific type of risk, neglecting possible interactions between different types of risk. From the mentioned papers we deduct the question in how far European

[2]While testing for robustness, the authors also examine whether the findings hold in the ZLB environment and the usage of shadow-rates is valid.

asset markets' pricing mechanisms are prone to unexpected changes in short-rates, conditional on different types of elevated and interacting risks, respectively.

This paper is structured as fols: we briefly introduce the assets that are the focal point of this paper. Then, we recapitulate the nexus between asset price determinants and risk and elaborate three distinct categories of common risks that all the respective asset prices are exposed to. In a next step, we extract factors via principal component analysis from a set of candidate variables assigned to the respective kinds of risk. With this approach, we want to reveal the latent phenomenon risk. We then incorporate these risk factors into TVAR-models that differ by the respective risk threshold variable. This results in a set of models, namely three per asset. Using vectorautoregressions is necessary to account for the endogenous relationship among asset prices, monetary policy, and different types of risk. The models are estimated using Bayesian techniques and are identified via an assumed recursive ordering within a er triangular matrix. After illustrating and discussing the issue of risk delimitation, we present asset-specific response functions to a hike in the short-rate. To account for the ZLB, we use a shadow short-rate when the effective er bound is binding, and EONIA otherwise. We conduct a battery of robustness checks to test the sensitivity of our results with respect to variables and ordering.

Our main findings are that there is a pronounced state-dependency of asset prices to monetary policy shocks and that different assets seem to show these non-linearities across states for different kinds of risk. This indicates that the susceptibility of asset prices to changes in short-rates depends on the currently prevailing risks. For instance, the junkier the corporate bond, the more accentuated are differences between high and macroeconomic risk regimes. On the other side of the rating spectrum, AA-rated corporate bonds only show minor differences between the macro risk regimes, but also between financial risk. In contrast, AA-rated bonds show a strong state-dependency when we distinguish between periods of high or political risk while non-investment-grade bonds display only a minor difference across high or political risk states. For equity, we find diverging results, depending on the respective sector: equity of industrial firm shows, depending on the model, less intense reaction to monetary policy shocks in regimes of macroeconomic or high political risk while equity of European banks is, surprisingly, positively affected by monetary policy shocks when financial risk is elevated.

2 European Asset Markets

In this paper we focus on two distinct types of assets and their risk regime-dependent sensitivity to monetary policy shocks: equity and corporate yields. Within equity, we differentiate between an index with focus on industrial firms, EUROSTOXX Industrials (ESIndustrials), and a bank equity index, EUROSTOXX Banks (ES-Banks), both total return indices. We use total return indices to also account for payed dividends. Regarding yields, we focus on long-term corporate bonds from two rating classes. 10 year AA-rated corporate bond with a 10 year maturity[3] and more risky corporate bonds summarized in a high-yield index[4] with maturities between 7 and 10 years.

The four series are in Fig. (1). As we can see, both equity series show the common feature of a strong downward reaction during the Financial Crisis. However, while we can observe a recovery in industrial equity, bank equity faced an additional downward adjustment during the European Government Debt Crisis and has yet not recovered from these disruptions. This probably reflects investors' doubt about future profitability as well as concerns about the actual soundness of the European financial system in general. Corporate bond yields face a common downward trend over our sample that goes hand in hand with the sharp ering of policy rates. Also here, we can see crises effects, as both series show hikes with different size during crisis periods that are very pronounced for riskier corporate bonds, especially during the Financial Crisis. Checking for robustness, we also take a look at the reaction of STOXX Banks and STOXX Industrials, and at corporate bond yields with rating BBB, the er bound of investment-grade bonds. Since we use euro area government bonds as variable in order to extract political risk in Sect. (3), we do not include them in this paper as asset of interest.

3 Risk Factors

To get a better understanding of the link between asset pricing and the types of risk we focus on within this paper, we revise how financial markets determine the value of an asset, what role perception of risk plays within these mechanisms, and how asset prices are expected to react to changes in their determinants.

The value of an asset V_i at time t, e.g. a stock or bond, can be described as a

[3]AAA is only available until April, 2016. We use AA-rated bonds as proxy.

[4]ICE BofAML Euro High Yield Index Effective Yield, obtained from FRED Economic Data.

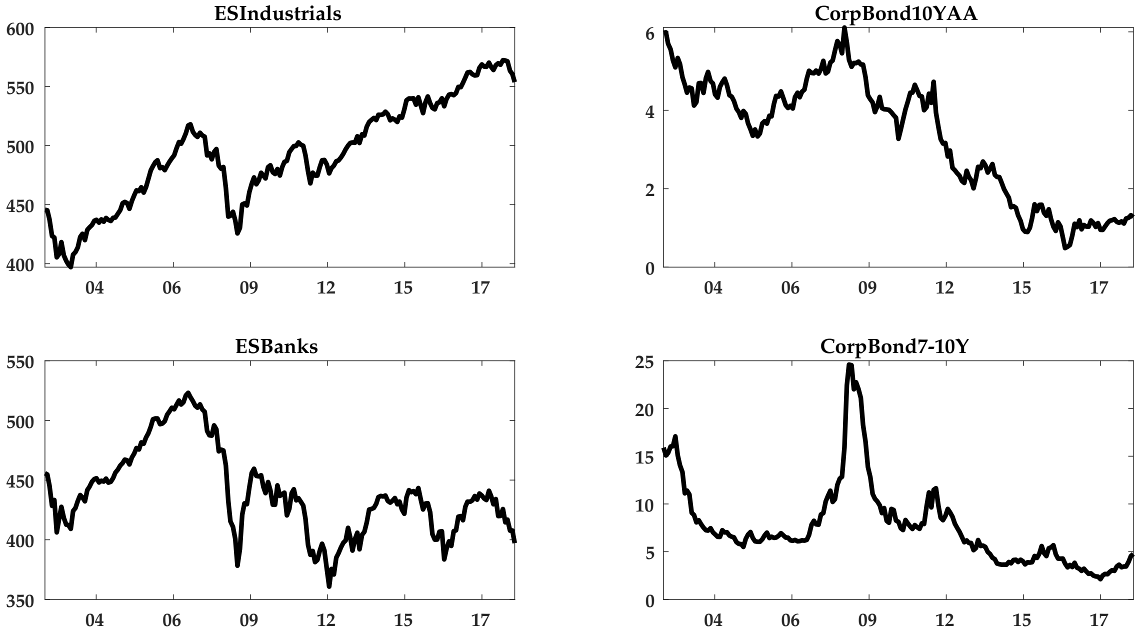


Figure 1: Euro area assets: EUROSTOXX indices for industrial firms and banks (left column, in logs*100) and yields of corporate bonds (right column, in per cent). *Notes:* stock indices are total return indices, while bond yields are yields to maturity.

function of expected future cash-fs (CF), discounted with expected future discount rates $r_{i,t}$. Assuming efficient capital markets, asset prices should only fol a random walk, except new information enters the pricing mechanisms or the assessment of existing information changes. Eq. (1) reflects these considerations:

$$V_{i,t} = f(E\left[\int_t^d r_{i,t}dt\right], E\left[\int_t^d CF_{i,t}dt\right]) + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma_{V,t}) \tag{1}$$

According to Cochrane (2011), asset valuation is primarily dominated by its respective discount factors r_i that are linked to the riskiness of investments and expected short-rates. Foling these ideas, one key feature is the understanding, correct delimitation and measurement of *risk* and the respective premia linked to bearing it. Expectations about the discount factor $r_{i,t}$ for an asset with duration d at time t can be divided into several components, as depicted in Eq. (2):

$$E\left[\int_t^d r_{i,t}dt\right] = E\left[\frac{d}{d-t}\int_t^d \mathrm{rfr}_t dt\right] + \mathrm{tp}_{d,t} + \mathrm{rp}_{i,t} \tag{2}$$

rfr_t refers to the (average) risk free short-rate invested over the horizon d, $\mathrm{tp}_{d,t}$ is the term premium that reflects interest rate risk and $\mathrm{rp}_{i,t}$ is a risk component. For the same maturity, rfr_t and $\mathrm{tp}_{d,t}$ should not differ across assets. In contrast, $\mathrm{rp}_{i,t}$ is an asset-specific, time-varying risk premium. While $\mathrm{rp}_{i,t}$ is often treated as a single variable, from an empirical perspective, this single component is affected by a vast spectrum of different types of risks. The assessment of these risks can further be distinguished between k risk factors that are common to all assets, we call them common risks, (CRs), but to a varying extend ψ_j, and an idiosyncratic risk component (IR). The idiosyncratic element captures asset-specific properties and the CR can have a varying relevance for different assets. For example, bonds of sound firms should face a er susceptibility to macroeconomic risk than bonds of firms under tension. One might also think that risk in financial markets is more relevant for the financial sector than for, e.g., industrial firms. Thus, an asset-specific risk premia is a function of the CRs, the relevance of a specific type of risk for the respective asset, and idiosyncratic risk, as outlined in Eq. (3)

$$\mathrm{rp}_{i,t} = \Sigma_{j=1}^{k}\psi_{j,t}CR_{j,t} + IR_{i,t} + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma_{i,t}). \tag{3}$$

Foling the elaborated mechanisms of this standard asset pricing nexus, we expect that increases or peaks in CR_j affect asset prices in the foling manner:

$$E_t\left[\frac{\partial(V_i)}{\partial(CR_j)}\right] = \psi_j \begin{cases} < 0, & \text{if } V_i \text{ is a stock index or a corporate bond.} \\ > 0, & \text{if } V_i \text{ is a bond yield.} \end{cases} \tag{4}$$

Eq. (4) states that increases in CR_j, or its perception, should er stock prices or increase bond yields. The same considerations hold for changes in current or future expected short-rates, as stated in Eq. (5):

$$E_t\left[\frac{\partial(V_i)}{\partial(\overline{rfr})}\right] \begin{cases} < 0, & \text{if } V_i \text{ is a stock index or a corporate bond.} \\ > 0, & \text{if } V_i \text{ is a bond yield.} \end{cases} \tag{5}$$

Increases in these rates should er stock prices or increase bond yields through their impact on discount rates and cash-fs.

A key problem is that monetary policy rates, different types of risk, and asset prices interact with each other, i.e. correlate at least during some periods. One prominent example for this nexus is the entanglement between European governments, their national banking systems and monetary policy actions of the ECB during the European Sovereign Debt Crisis. As a result, the mechanisms are simplistic and do not reflect the endogenous relationship among them, especially when we take an aggregate perspective with e.g. broad stock indices or corporate bond yields that we have introduced in Sect. (2). Thus, this is the main motivation to use a VAR-model that is described in more detail in Sect. (4). Besides the problem of endogeneity, we also have to address the question whether or not this interaction varies across different risk states. If so, this can implicate state-dependent sensitivity of assets to monetary policy shocks.

In a standard VAR-model there is no room to account for problems like state-dependency or non-linearities among the interaction between these variables. Hence, a standard VAR-model cannot distinguish between the impact of unexpected changes in short-rates, for instance, induced by policy rate hikes, during high or states of risk.

This is were we contribute. We want to show, if and in how far the reaction of different asset prices to monetary policy shocks, in size as well as in sign, depends on the degree of distinct types of CRs inherent in European markets.

Estimating risk premia directly is a challenging task, especially when we have to distinguish among the respective subcategories. Thus, we rather estimate CR directly from sets of candidate variables and include them into our VAR-model. Within this paper, we differentiate between $k = 3$ types of CRs that should all have an impact on asset markets.[5] The three kinds of risk are depicted in Fig. (2).

We think that this categorization among risk is sufficient, albeit some periods, primarily crises periods, are characterized by a large degree of correlation among them. We will illustrate this in Sect. (5.1).

These types of risk are per se not observable and not directly measurable. Thus, we interpret them as **one** common component that drives a set of observable candidate variables. We therefore extract a single principal component from a set of (standardized) series of size n that are assumed to be driven by the respective risk. They are collected in $\mathbf{X}_{t\times n}$, with t indicating the time horizon. Next, we conduct an eigenvalue-decomposition of the respective covariance matrix $\mathbf{X^TX}$:

$$(\mathbf{X}^T\mathbf{X})\mathbf{v} = \lambda\mathbf{v} \tag{6}$$

In Eq. (6), $\mathbf{v}$ equals the matrix of eigenvectors, often referred to as loadings, and λ is the vector of eigenvalues of $\mathbf{X}^T\mathbf{X}$. The eigenvector that corresponds to the largest eigenvalue is interpreted as a primary driver of the set of variables in $\mathbf{X}$. Thus, this risk factor $\mathbf{F_t}$ is constructed as fols:

$$\mathbf{F_{t\times 1}} = \mathbf{X_{t\times n}v_{n\times 1}} \tag{7}$$

This approach is generally used by central bankers, researches and practitioners

[5]Idiosyncratic risks, e.g. liquidity premia, are neglected in the foling. They should play a minor role for the broad indices we use within this paper.

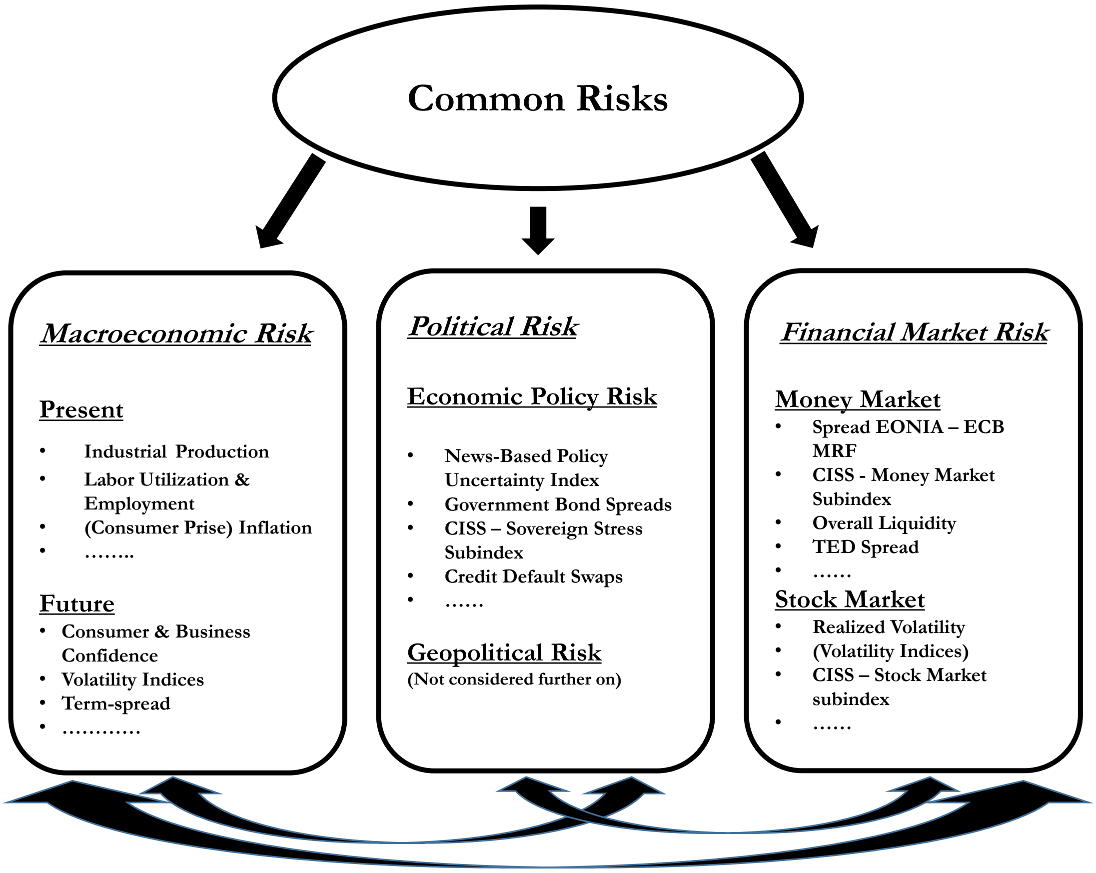


Figure 2: Common risks and their categorization, differentiation, and candidate variables for their measurement.

around the world. For example, Brave and Butters (2011) use principal component analysis (PCA) to construct a Financial Conditions Index (FCI) for the US.

In contrast to most applications of factor (or principal component) analysis that simultaneously extract a set of (often orthogonalized) factors from a (large) data matrix, we rather extract "risk" itself to use it as a variable for further analysis. Thus, we preemptively select variables and assume that they are primarily driven by only **one** type of risk. This is a quite strong assumption, but we do so because the three assumed risk factors face a high degree of correlation in crises periods and a respective rotation of factors that makes them orthogonal to each other would vanish these important interdependences between various types of risks during these episodes. Henceforth, we are not primarily interested in reducing the data dimension. Instead, we extract one latent but common driver in the respective variables and al them to interact within a VAR framework. Of course, the correct and diligent delimitation, assignment, and categorization of variables is a key element within this approach. For example, Koop and Korobilis (2014) suggest a sophisticated way to address these concerns in a dynamic setup. In particular, they select suitable variables that are used to construct their FCI and let the contribution as well as the selection of variables vary over time. However, given that we want to distinguish between different risks in a categorical way instead of a pure econometric perspective, this approach does not fit to this paper. We do not want to mechanically replaces variables during e.g. crisis or drop out others when they do not contribute in a meaningful manner, e.g. during some calm or complacent times.

In the foling, we will present candidate variables that are assumed to primarily driven by a certain type of risk. Next, we capture the first principal component to which we refer in the foling as risk factor $\mathbf{F_t}$. These ideas are depicted in Eq. (6) and Eq. (7). We show and discuss these factors for each type of risk depicted in Fig. (2), but also display the unexplained variation in the underlying variables, see Eq. (8), that is not explained by the common factor. We think that presenting the unexplained variation for each variable of the respective set of variables assigned to the specific type of risk, calculated as

$$\epsilon_{\mathbf{t}\times\mathbf{n}} = \mathbf{X}_{\mathbf{t}\times\mathbf{n}} - \mathbf{F}_{\mathbf{t}\times\mathbf{1}}(\lambda_{\mathbf{n}\times\mathbf{1}})^{\mathbf{T}} \tag{8}$$

is an easy, but illustrative way to show during which periods the respective variables are quite well explained by the single component and when not. As we face standard-normally-distributed variables to construct $\mathbf{F_t}$, we also show $+/-$ one sigma bands to make the degree of unexplained variation more interpretable within the graphics. Furthermore, we present the outcomes for the three distinct PCAs up to n components in Tab. (8) to Tab. (10), appendix. As it can be seen, the first component captures in all three different categories of risk the absolute majority of variation in the respective data series.

3.1 Macroeconomic Risk

We interpret macroeconomic risk as risk that stems from business cycles. Hence, we select variables similar to Stock and Watson (2002) who construct macroeconomic factors for the US. They emphasize that one or a few factors are sufficient to capture the common dynamics of the set of underlying macroeconomic series.

For current real activity and price dynamics we use Industrial Production, Consumer Prices (HICP), unemployment, hours worked, the €coin Indicator, and new orders as well as capacity utilization of the industry.

The sentiment and confidence about the near future with respect to the then pre-

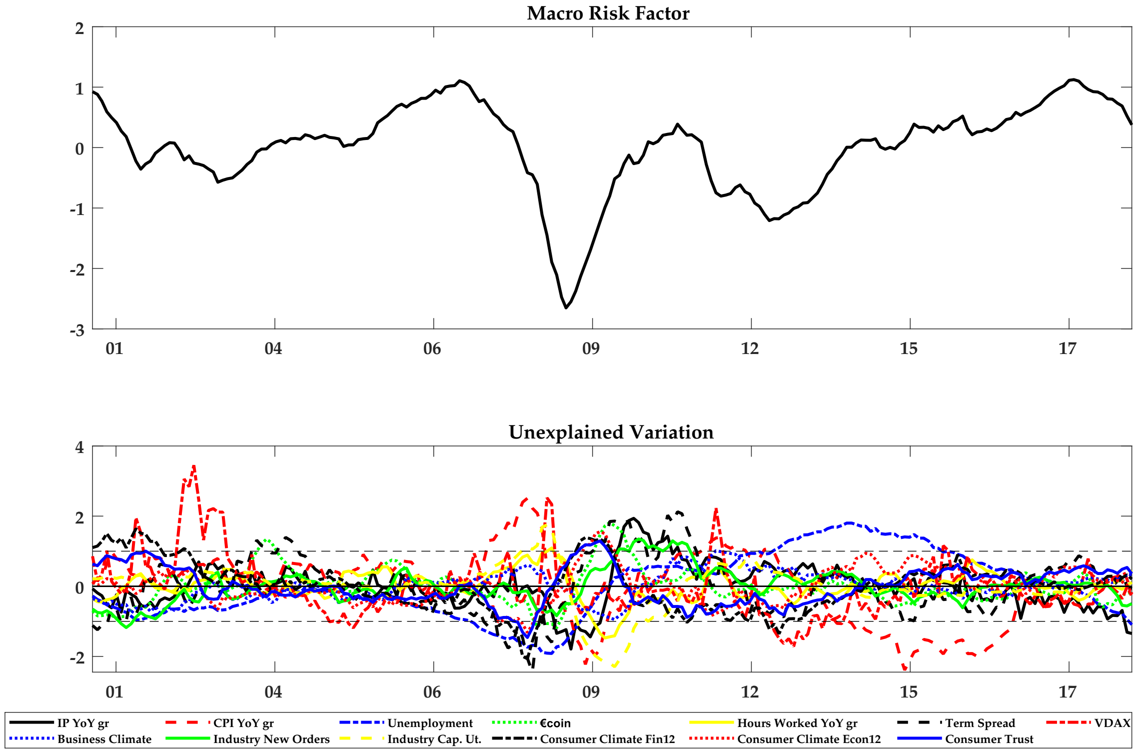


Figure 3: First principal component, referred to as Macro Risk Factor (MRF), of variables in Tab. (5) (upper picture) and residuals $\epsilon_{t\times n}$ of variable movement that is not explained by the common component (er picture).

vailing macroeconomic conditions is reflected by financial market variables as well as survey data. We include the term spread, often referred to as the slope of the yield curve, as it has a high predictive power for future macroeconomic performance and thus is often acknowledged as a leading indicator for recessions, see e.g. Estrella and Hardouvelis (1991). The VDAX, a 12 month-ahead implied volatility index for the German DAX[6], captures uncertainty via (diverging) views about future stock markets. Besides the business climate, we also include three distinct consumer climate questionnaires: the expected individual financial situation 12 months ahead, the expected overall economic conditions in 12 months, and consumer trust. These surveys are provided by the European Commission. Our variables and their respective transformation as well as their source are listed in Tab. (5), appendix. Moreover, Fig. (3) shows the resulting estimate for our macroeconomic risk factor and the respective residuals for each variable we use.

[6]The measure of first choice, VSTOXX, a volatility index for the EURO STOXX 50, is only available since 2008. However, for the time period available, both series correlate more than $\rho > 0.95$ such that we use the VDAX as proxy for VSTOXX.

3.2 Political Risk

Compared to macroeconomic risk, the measurement and delimitation of political risk is a more difficult task. We focus on economic policy risk, other dimensions of political risk, like geopolitical disputes or domestic tensions besides economic policies are not considered further on. Measuring this specific type of political risk can be divided in principle into two strands.

The first one uses variables that are linked to sovereign solvency, e.g. government yields or credit default swaps. As their data is reliable and easy to obtain, they are wide-spread measures of economic policy risk. Aizenman et al. (2013), for instance, regress euro area and non-euro-area credit default swaps (CDS) on a set of fiscal variables for various samples. A key finding is that the relevance of these fiscal measures for the determination of CDS is high, albeit it fluctuates over time. While the relevance of these measures was little pre-2008, they explain quite well the CDS during the European Sovereign Debt Crisis. A similar approach is used by Bernoth et al. (2012) who focus on government bond yield differentials though. They find that the respective risk premia, which is reflected by the spread to German BUNDs, inversely relates to fiscal imbalances and liquidity.

The second strand augments measurement of political risk with data that stems from text mining and text analyzing methods. These approaches quantify this specific type of risk by analyzing relevant text data, primarily newspaper articles, with respect to relevant key words and their corresponding attitude. One prominent example is the work of Baker et al. (2016) who construct an index by evaluating distinct newspaper articles with word counting mechanisms. We combine both strands within our extraction of political risk.

In the foling, we describe the variables we assign to political risk and their respective construction in more detail. They are summarized in Tab. (6), appendix. Baker et al. (2016) provides various News-Based Policy-Uncertainty-Indices for Europe, Germany, France, Italy, Spain, and the UK. As we are primarily interested in the economic policy risk inherent in the euro area, we construct a proxy by using the respective indices of Germany, France, Italy, and Spain, representing the largest economies, and weight them with their (re-scaled) country weight in the HICP.

We also construct a representative euro area government bond spread of selected euro area member states to Germany. We do so for government bonds with a 10-year maturity. Therefore, we weight the national bond yields of Italy, France, Spain, Portugal, Ireland, and Greece with their share on the total amount of outstanding debt of these countries. Compared to other government bond yields, we assume the

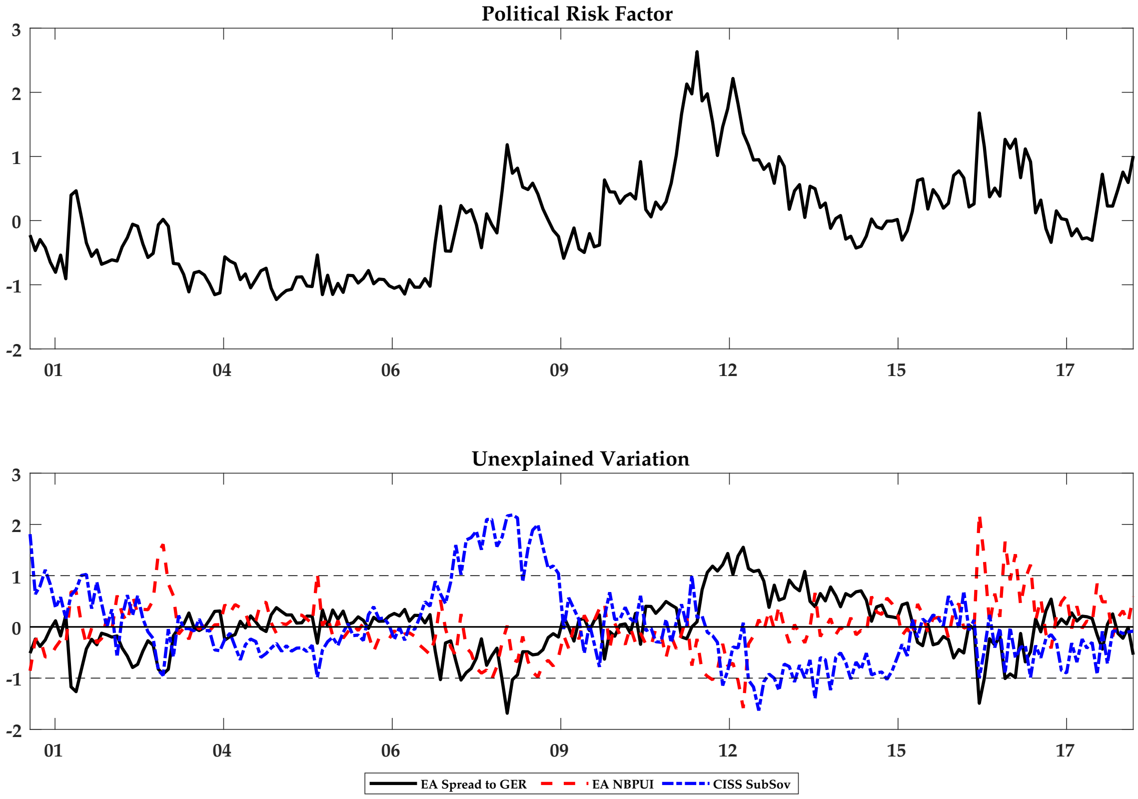


Figure 4: First principal component, referred to as Political Risk Factor (PRF), of variables in Tab. (6) (upper picture) and residuals $\epsilon_{t\times n}$ of variable movement that is not explained by the common component (er picture).

German BUND to be "risk free" and, thus, subtract it from this the series.
Our third variable is the Composite Indicator of Sovereign Stress (SovCISS). This variable aggregates a vast variety of different sovereign stress dimensions, such as credit risk, volatility or liquidity aspects of government bond markets across different maturities, into one indicator. For a detailed description of this variable, see Garcia-de Andoain and Kremer (2017).
Unfortunately, given that the aforementioned CDS are only available from 2008 onwards, we do not want shorten our sample and, thus, do not include it in our analysis. The estimated political risk factor is displayed in Fig. (4), amended with the residuals of the variables involved in the estimation.

3.3 Financial Market Risk

Our third and last category is the analysis of financial risk, where we differentiate between various aspects. We use subindices of the CISS[7] to either capture stock

[7]Composite Indicator of Systemic Stress, an indicator provided by the ECB to measure overall stress via various subindices.

market stress, interbank-business disruptions, or money market tensions. We do not include the (government) bond market subindex because we assume that this kind of stress is related to political risk and thus is better captured by the SovCISS. Risk evasion, "flight to safety", and liquidity concerns are reflected in a European TED-Spread, which is the difference between three month EURIBOR and three month German government bond yield.

During normal times and in a sound working environment, liquidity shortages as well as excess liquidity play a minor role in European money and interbank markets, and they can be measured e.g. via the (absolute or squared) spread between EONIA and the Main Refinancing Facility (MF). However, given that the ECB has began to counteract the turmoils of Financial Crisis since 2008, this potential variable is severely distorted. Thus, to account for unconventional monetary policy that was directed to mitigate liquidity shortages and calm down financial markets via massive access to central bank liquidity, we construct a variable that captures the extended usage of various money market measures (MMMs). Prominent measures regarding the funding side are the various (Targeted) Longer-Term Refinancing Operations ((T)LTRO), offered to banks by the ECB, but also hikes in the Marginal Lending Facility (MLF) that indicate high liquidity demand. On the other hand, excessive usage of the deposit facility (DF) can be interpreted as money market lending side risk. In order to correct for the conventional conduction of monetary policy that, in particular, dominates pre-2008 periods, we subtract the MF and thus isolate the extraordinary nature of ECB's policy since 2008.[8] Thus, our variable takes the form

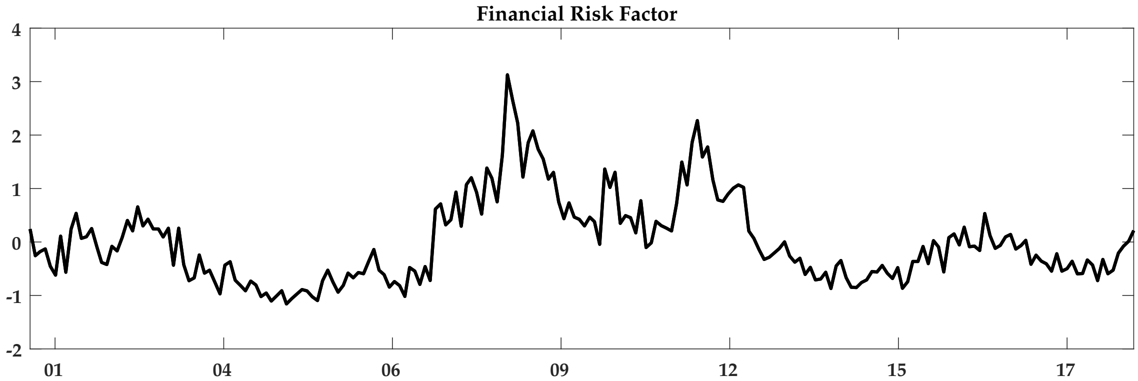
$$\text{ECB MMM} = (\text{DF} + \text{MLF} + \text{(T)LTRO}) - \text{MF}$$

and is depicted in Fig. (23), appendix, for the sake of illustration. A detailed description of the variables can be found in Tab. (7), appendix.

One additional variable that might be omitted at the first glance is the simultaneous probability of default of two or more large European banks[9] provided by the ECB. Since we think that this variable has to be assigned to systematic risk, we do not

[8]Note that we cannot account for the introduction of e.g. full allotment procedures or altered requirements for eligibility of assets by the ECB in October, 2008. As we only focus on the quantity of usage of programs and facilities, not on qualitative changes in their conduction, our measure may underestimate the degree of intervention by the ECB. On the other hand, as we subtract Main Refinancing Operations that are also affected by these operational changes, we exclude the intensive usage of them. Which aspect dominates remains unclear.

[9]ECB Statistical Data Warehouse identifier: RDF.D.D0.Z0Z.4F.EC.DFTLB.PR.



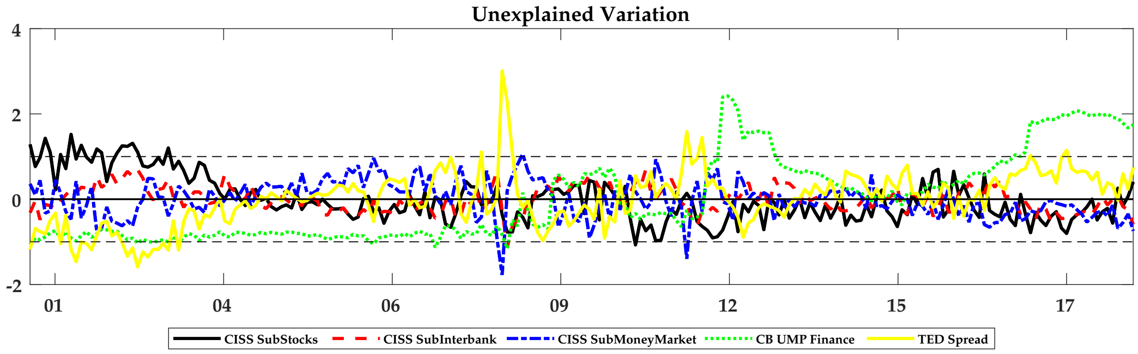


Figure 5: First principal component, referred to as Financial Risk Factor (FRF), of variables in Tab. (7) (upper picture) and residuals $\epsilon_{t\times n}$ of variable movement that is not explained by the common component (er picture).

consider it within this paper. Nevertheless, we see the challenge to clearly differentiate among various concepts of the phenomenon risk.

The resulting financial risk factor and the respective residuals of the used variables can be found in Fig. (5). The factor looks quite similar to the Banque de France's FCI for the euro area, suggested by Petronevich and Sahuc (2019). Their index is estimated via daily data with a more sophisticated principal component approach. It sums up information from 18 variables (with dynamic weightings) of similar categories as we use within this paper. Additionally, they include stock indices themselves, exchange rates, and inflation expectations. The ladder one, we would rather assume to be on the macroeconomic side. Again, this highlights that demarcating different types of risks is a challenging task, although the resulting variables look very similar. Unfortunately, given that the Banque de France's FCI is only available since 2008, we avoid losing pre-2008 observations and, thus, rely on our own series.

For the sake of illustration, we present our estimated risk factors in Fig. (6). We invert our macroeconomic risk factor for a better interpretation, because this type of

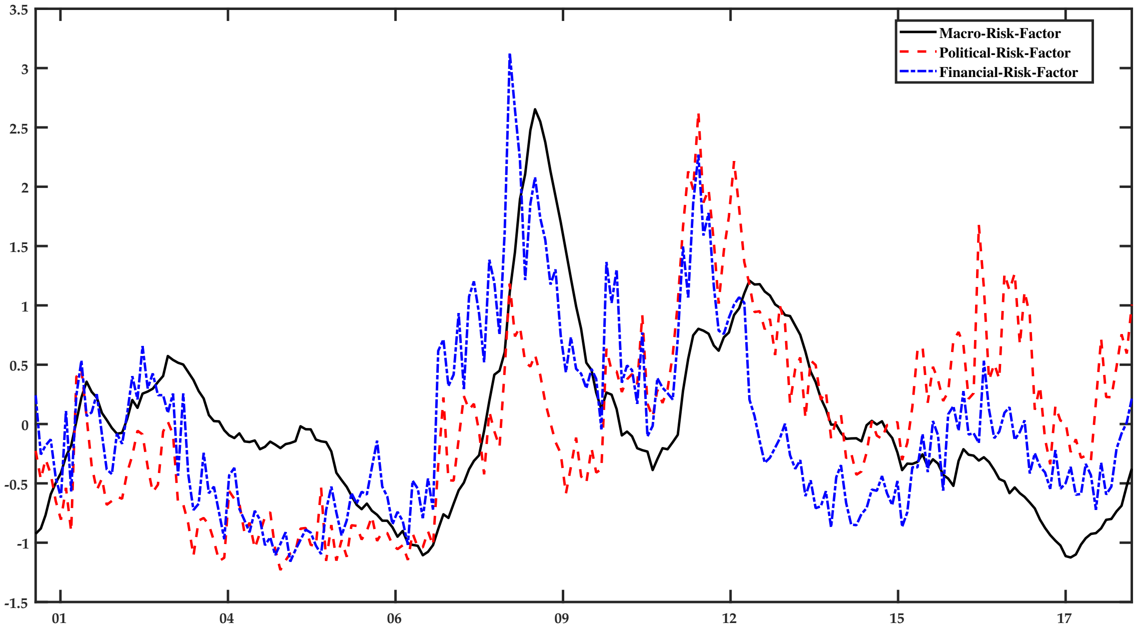


Figure 6: Estimated risk factors: MRF (black-solid), PRF (red-dashed), and FRF (blue-dotted).
Notes: the MRF deviates from Fig. (3) because we inverted it for ease of interpretation.

risk is high when our factor that tracks it is and vice versa. The resulting estimates mirror-image the dominating patterns of various crisis in Europe quite well. Macroeconomic risk fols the Great Recession and, to a smaller extend, the macroeconomic disturbances during the European Sovereign Debt Crisis. The political risk factor peaks during the European Sovereign Debt Crisis with its concerns about euro-area-integrity, but is also elevated within the Financial Crisis and at the current edge. It is est in the run-up to the Financial Crisis. Unsurprisingly, the financial risk factor skyrockets during the turmoils linked to the Financial Crisis but also reflects, to a smaller extend, severe distortions in European financial markets until the end of the European Sovereign Debt Crisis in mid-2013.

Note that all three risk factors have peaks during the Financial Crisis as well as during the European Sovereign Debt Crisis, with different timings and to varying scales. However, they show quite different movements during the rest of the sample. This indicates that during severe crises periods the interaction between different types of risk is quite high and that a clear delimitation of the phenomenon ”risk” especially within these outstanding periods remains a challenging task. We introduce a way to at least illustrate this issue in a more appealing way in Sect. (5.1).

4 The Factor-Augmented Threshold VAR-Model

We are interested in possible asymmetric responses of asset prices to a monetary policy shock, conditional on high or risk inherent in markets. Thus, we employ a TVAR-model that we augment with the aforementioned risk factors. We want to elaborate possible differences in reaction patterns. The model is similar to the model suggested by Alessandri and Mumtaz (2017). The foling subsections describe our model and the estimation methods.

4.1 Data and Model

In our model, we incorporate the three mentioned factors, a (shadow) short term interest rate and one of the assets mentioned in Sect. (2). Thus, our 5 variable TVAR-model takes the form

$$\begin{aligned} Y_t = & \left[c_1 + A_1(L)Y_{t-p} + B_1^{-1}\varepsilon_t\right] \times S_t \\ & + \left[c_2 + A_2(L)Y_{t-p} + B_2^{-1}\varepsilon_t\right] \times (\mathrm{I} - S_t). \end{aligned} \tag{9}$$

Y_t is a row vector with monthly data. Due to data availability, our sample starts in January, 2002, and ends in January, 2019. Y_t contains our MRF, a short-rate, we use EONIA[10], our PRF, and the FRF. Moreover, we include the four assets presented in Sect. (2) separately. Equity indices enter in logs*100, yields in percentage points. Thus, Y_t takes the form

$$Y_t = [MRF_t \; SR_t \; PRF_t \; FRF_t \; Asset_{i,t}]'. \tag{10}$$

$A_i(L)$ are the reduced-form coefficient matrices up to lag p, while $B_i^{-1}\varepsilon_t$ are the reduced-form error terms with covariance matrix $\Sigma_i = (B_i^{-1}\varepsilon)(\varepsilon B_i^{-1})'$, with i $\in$ {1,2}. The regime switch of our model is determined by our transition variable S_t. As depicted in Eq. (11), our model switches with a delay d across regimes if a threshold z^* is surpassed.

$$S_t = \begin{cases} \mathrm{I}, & \text{if } z_{t-d} < \; z^* \text{ ("-risk regime")} \rightarrow \text{Regime 1} \\ 0, & \text{otherwise ("high-risk regime")} \quad \rightarrow \text{Regime 2} \end{cases}. \tag{11}$$

Using this type of model, we can take into account the varying degree of correlation among different types of risk and the resulting effects on assets. As we will see in

[10] For periods characterized by the ZLB, EONIA is augemented with the shadow-rate by Krippner. The robustness section discusses the usage of an alternative shadow-rate provided by Wu and Xia (2016).

Sect. (5.1), different risk-regimes coincide. The VAR-coefficients of our two distinct regimes can capture these changing relationships.

Moreover, Eq. (10) also reflects the order of our baseline, er-triangular identification scheme via cholesky decomposition. Given this order, we obtain a structural model of the reaction of asset prices to changes in e.g. short-rates. Thus, we are able to capture the contemporaneous interdependences between the variables and obtain orthonormal shocks we are interested in later on. Further technical details regarding model estimation are lined out in Sect. (4.2). We justify this scheme by the foling considerations: macroeconomic variables are inert and only react to own shocks contemporaneously. To pursue its mandate, the central bank aims at controlling short-(shadow-)rates to ultimately influence economic performance. Hence, we assume that macroeconomic innovations and own shocks drive the short-rate. Variables assigned to (economic) political risk are driven by macroeconomic developments, changes in yields, and by themselves within the same period. Financial market risk can generally assumed to be affected by all of the above-mentioned variables as well as by itself. Additional to their own shocks, the last ordered variables, namely assets, are assumed to be impacted by the all model variables within the same period. We alter this identification scheme in Sect. (6). There, we apply two alternative orders.

4.2 Estimation

We estimate the model using Bayesian methods, very similar to Alessandri and Mumtaz (2017), chapter 3.3.[11] For comparability reasons across the large set of models[12] presented later on we estimate all of them with one lag of the endogenous variables, implying $p = 1$. We think this is not a very strict assumption because the variables of major interest, our assets, are either in inert log-levels or in percentage points and thus they are primarily driven by their own past values. Additionally, we set $d = 1$ for all subsequently presented models. This implies that the indicator function S_t switches the regimes with one month delay after passing the unknown threshold z^*.[13] Furthermore, we prior believe that z^*_{init} is around its median and al a

[11]We thank Blake et al. (2012) for providing very helpful codes that are the backbone of our estimation procedure.

[12]In sum we estimate $3 \times 4 = 12$ TVAR-models, for each of the 4 assets 3 different TVAR- models in the main section and additional $((3 \times 3 \times 2) + (2 \times 3 \times 4)) = 42$ TVAR-models in the robustness section. For sake of comparability across them, we initially calibrate them all the same.

[13]In Alessandri and Mumtaz (2019) d is estimated as well, with the FCI of the Chicago Fed as threshold variable. 95 % of the probability mass of the distribution of their estimator lies within one and two, with a median of 1. We use a similar framework, thus we think that this is not a harsh assumption.

quite loose variance $\sigma_z^2 = 10$. We think that this loose prior is appropriate because we want to take into account that risk is often reflected by fat tails of the risk variables' distribution. The priors for VAR-coefficients, namely $\mathbf{a}_1 = \text{vec}([c_1 \ A_1(L)])$ and $\mathbf{a}_2 = \text{vec}([c_2 \ A_2(L)])$, are assumed to stem from an ordinary equation-by-equation OLS regression of Y_t on its own lagged values within a standard, linear VAR-model. This implies $\mathbf{a}_1 = \mathbf{a}_2$, that we prior assume no sate-dependent differences within our VAR-coefficients. We limit the value space of permitted estimates to the interval [-1, 1]. Moreover, we use the estimated coefficient variances as prior for the variance of the coefficients.

Our reduced-form model is estimated with an iterative Gibbs-sampling-algorithm, which is in line with Chen and Li (1995). Within this algorithm the latent threshold z^* is estimated with a random walk Metropolis-Hastings procedure that generates a new estimate for the latent threshold. The regime-switching propensity of our model using this updated latent threshold variable z^* is updated if the new value of z^* provides higher log-likelihood values of the estimated posterior distribution of the two separate models, and discarded otherwise. As mentioned above, in order to obtain an identified model with structural, orthonormal shocks, we apply a cholesky er-triangular decomposition to the two distinct reduced-form covariance matrices Σ_i. We do so after our Gibbs-sampling exceeds the number of burn-in iterations (here: 18,000) and step into a impulse response analysis during the foling 2,000 iterations. We decompose the respective estimated covariance matrix Σ_i into a er-triangular matrix B_i. This matrix is then multiplied with the estimated reduced-form VAR-coefficients $A_i(L)$ and $B_i^{-1}\varepsilon_t$, such that $B_i\Sigma_i B_i' = I$ holds. As a result, we obtain two representations of our model, with structural parameters Θ^i, for each iteration step. To derive impulse response functions for the variable of interest within these iterations, we use Monte Carlo Integration, as described in e.g. Koop et al. (1996). Given that the propagation paths of shocks across the system are no longer obtainable using the moving average representations of the model, as e.g. done in linear, state-invariant (stationary) VAR-models, it is inevitable to proceed this way. We have to take into account that shocks hitting at different points in time, in a respective risk state i with the corresponding VAR-parameters Θ^i linked to it, affect the dynamics of the whole set of future values after a shock e.g. in the short-rate, for a horizon h. This is in particular the case for our endogenous threshold variable z^*. Thus, we need two different conditional expectations, shown in Eq. (12), for randomly chosen points in time to simulate impulse response functions.

$$IRF^i_{t,t+h} = E\Big[Y_{t,t+h}|\Theta^i, z^*, d, u\Big] - E\Big[Y_{t,t+h}|\Theta^i, z^*, d\Big], \text{ for } h = 0, ..., 30. \tag{12}$$

These two conditional expectations differ only with respect to the dynamics induced by a shock vector u[14] that enters the first part of Eq. (12). Note that the impulse response functions to a shock u do not only depend on the set of different VAR-parameters captured in Θ_i and z^* with its assumed delay d, but are also sensitive to the simulated horizon up to h. Next, we average over the randomly obtained impulse response functions for each regime. For a general and illustrative description of the ideas, procedures and algorithms, see e.g. Kilian and Lütkepohl (2017).

With this modeling, we can take into account that the regime-switch within our model over our sample can endogenously differentiate between the effect that short-rate shocks have effects not only on our variables but also on the propensity to switch across regimes over the horizon h. We think that it is plausible to account for the effects of short-rate shocks on our threshold variables instead of simply considering the dynamics of shock propagation in two distinct regimes with their respective VAR-coefficients Θ^i. The set of the difference between different propagation paths of our assets to an initial short-rate shock compared to a non-shock scenario then leads to the impulse response functions presented later on for each regime.

5 Regime-Dependent Transmission of Monetary Policy Shocks

To get a better understanding about the regime-switching propensities of the set of models we have estimated, we start with presenting the model-implied thresholds and the respective transition probabilities. We focus on the estimations for the mean threshold and the corresponding mean transition probabilities between the two regimes. We then introduce two ways to illustrate a possible problematic issue of interconnection among risks, that is most pronounced during the two major crisis periods in Europe.

Next, we subsequently asses the impact of monetary policy shocks on the various assets for three distinct threshold variables: political risk, macroeconomic risk, and financial market risk. Further on, we will refer to a -risk regime when the indicator variable is be the estimated threshold of the respective variable, otherwise we are in a high-risk regime, as stated in Eq. (11). We assume in all cases a one percentage point change[15] of the short-rate and its impact on the different assets, conditional

[14] u is a zero vector except for the second entry, the short-rate. There is a one reflecting the shock in this variable, in the robustness section this one changes the position to reflect the altered order.

[15] As the two different regimes are linear models, the response functions can be re-scaled to e.g. a 25 bp shock.

on the respective regime. The impulse response functions for high-risk regimes are red-shaded while the impulse response functions for risk regimes are black lines. In both regimes, we present the median reaction and the 16^{th} and 84^{th} percentiles of the distribution of our 2,000 simulated impulse response functions.

5.1 Entangled Risk Regimes: An Illustration

As we are interested in the sensitivity of four different assets, conditional on three different types of risk, we estimate in sum 12 TVAR-models. For each of these 12 models, Fig. (7) to Fig. (10) show the respective threshold variable of the model, the estimated median threshold and the median transition probabilities. Besides minor deviations, all models identify similar periods of high or risk for the respective threshold risk variable, independent from the asset incorporated into the model. Thus, the identification properties of our models with respect to risk regimes are not very sensitive to the asset selection.

For the first column of Fig. (7) to Fig. (10), we can see that after the dot.com burst and before the outbreak of the Great Recession there was a prolonged period of macroeconomic risk. Moreover, we see that this type of risk sky-rockets during the disruptive events of this outstanding crisis. Again, it fols a short period of macroeconomic risk until the European Sovereign Debt Crisis and its dampening impact on economic performance. After the abate of this debt crisis, our macroeconomic risk factor remains in a state until the current edge.

The second column of Fig. (7) to Fig. (10) contains the threshold and regime-switching propensities when political risk is used as threshold variable. Before the outbreak of the Financial Crisis, there were prolonged periods of policy risk. Contrary to this, since the start of the Financial Crisis, our model estimates that we are permanently in a high-risk regime and (almost) never return to -risk periods equivalent to pre-2008-times. In general, most models estimate that high-risk regimes dominate the sample space.

We can see the behavior of our models when we distinguish between periods of high and financial risk in the third column of Fig. (7) to Fig. (10). It stands out that, in contrast to the other risk factors, we see a quite long period of high financial market risk, that starts with the Financial Crisis and prolongs until the end of the European Sovereign Debt Crisis in 2013. During this period, we never drop back into a -risk regime. This fits the narrative that the Financial Crisis and the European Sovereign Debt Crisis are highly interconnected via the European financial markets, especially the banking sector. Only since the introduction Draghi's famous

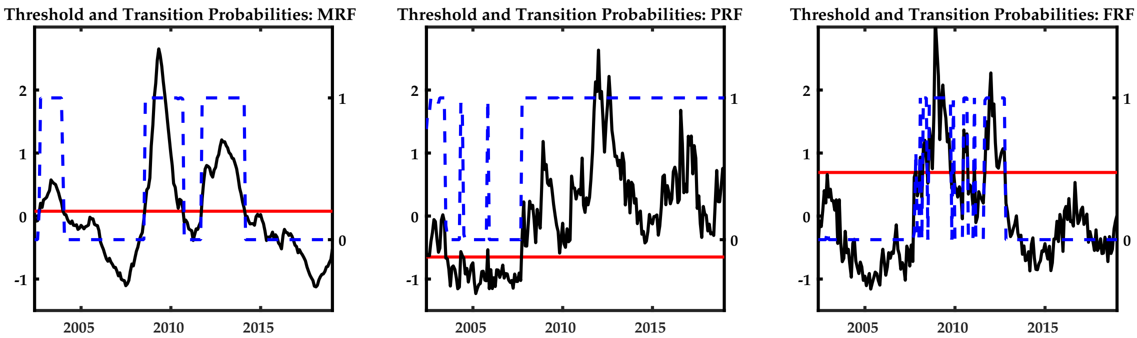


Figure 7: TVAR-models with ESBanks.
Notes: black-solid is the respective risk factor (left axis), red-solid is the median estimate for the latent threshold (left axis), blue-dotted reflects the median transition probability between regime 1 and regime 2 (right axis).

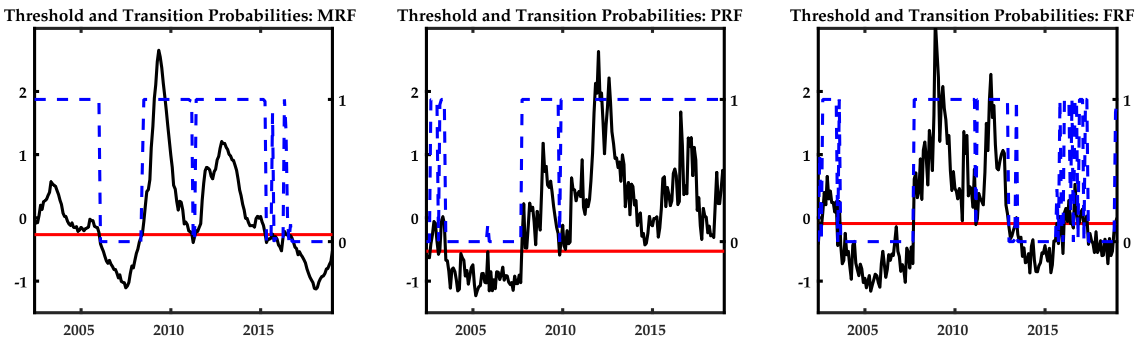


Figure 8: TVAR-models with ESIndustrials.
Notes: black-solid is the respective risk factor (left axis), red-solid is the median estimate for the latent threshold (left axis), blue-dotted reflects the median transition probability between regime 1 and regime 2 (right axis).

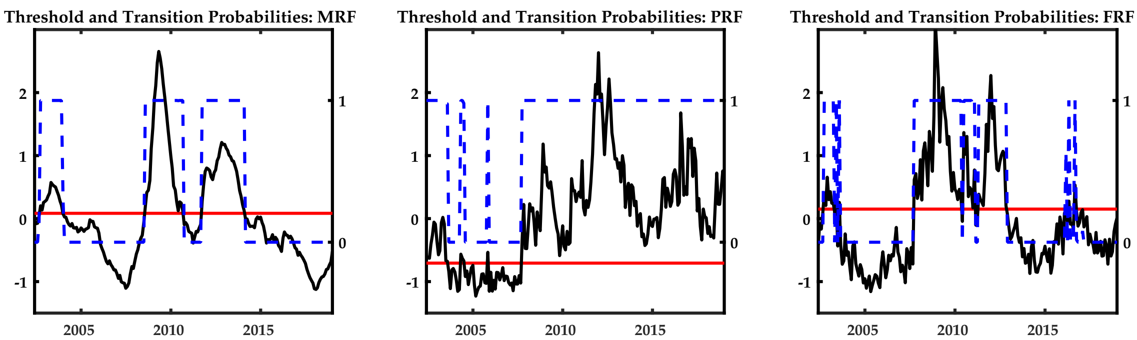


Figure 9: TVAR-models with CorpBond10YAA.
Notes: black-solid is the respective risk factor (left axis), red-solid is the median estimate for the latent threshold (left axis), blue-dotted reflects the median transition probability between regime 1 and regime 2 (right axis).

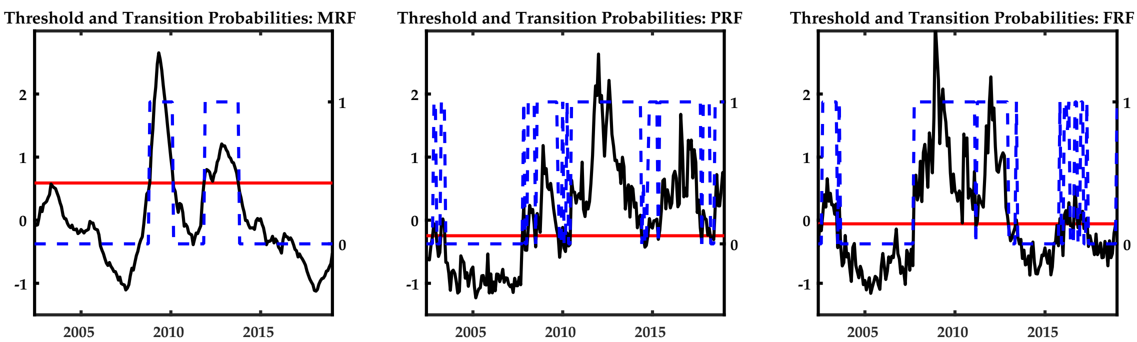


Figure 10: TVAR-models with CorpBond7-10YHY.
Notes: black-solid is the respective risk factor (left axis), red-solid is the median estimate for the latent threshold (left axis), blue-dotted reflects the median transition probability between regime 1 and regime 2 (right axis).

"Whatever it takes" statement in July, 2013, financial market risk calmed down for a prolonged period. Nevertheless, at the current edge as well as between 2016 and 2018, our model often switches between high- and -risk states. This indicates elevated uncertainty about financial stability in European financial markets.

As our binary variable that indicates the respective regime switches frequently in the models with the FRF as threshold variable, especially at the current edge, concerns arise about the sharp "jump-like" switches between states within a short period. In the appendix, we present an alternative approach to our binary transition setup that stem from a smooth-transition function which is depicted in Fig. (17). Incorporating this transition function into our VAR-framework and deriving impulse response functions, as in Auerbach and Gorodnichenko (2012) for different states of the US business cycles, would require ad hoc assumptions about regime boundaries, in our case for the FRF. As we have not yet found any suitable indicator in the literature but our own binary one, we rely on the results of our models.

As already mentioned in Sect. (3), one possible problem is that different types of risk are interconnected, especially during crises periods. We can see this in Fig. (7) to Fig. (10) where some overlapping periods exist for the three distinct types of risk we deal with. To illustrate this, we introduce a binary measure that displays this issue over our sample. This measure, we call it absolute regime overlap (ARO), equals 1 if two different risks are high simultaneously[16] at sample point t, and 0 otherwise:[17]

$$ARO_{i,j,t}^{asset} = \begin{cases} 1, & \text{if } \mathrm{S}_{i,t} = 0 \wedge \mathrm{S}_{j,t} = 0 \text{ with } i, j \in \{MRF, PRF, FRF\}, \quad \forall i \neq j \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

Fig. (24) to Fig. (27) of the appendix show these periods of coinciding high-risk regimes for our set of estimated models. Almost all figures have hikes during the Financial Crisis and the European Sovereign Debt Crisis, sometimes with minor interruptions between the two crises. On the contrast, we only have sporadic periods of simultaneous skyrocketing of more than one type of risk at the beginning and at the end of our sample. On the one hand, this emphasizes the outstanding nature of these two crises. On the other hand though, this makes a sharp and

[16] According to the estimated threshold of the respective model.

[17] Note that these two different risk regimes stem from the same data collected in Y_t, but from different TVAR-models that differ by the threshold variable.

distinct delimitation of specific risks during extraordinary crisis periods even harder.

To sum up these interdependences between the respective risk threshold variables in a more appealing way, we relate them to the (adjusted) sample size. Thus, a relative regime overlap (RRO) is constructed by dividing the sum of the different AROs by the sample length, corrected for the lag-length of the model, p:

$$RRO_{i,j}^{asset} = \Sigma_{t=2002M4+p}^{2018M1} ARO_{i,j,t} \times (nobs - p)^{-1}, \text{ with } p = 1 \tag{14}$$

The results are listed in Tab. (1) to Tab. (4). The main diagonal of the tables is the share of high-risk regimes of the respective risk threshold on the overall sample. The overlap between regimes is reflected by the er triangular block.

ESBanks	MRF	PRF	FRF
MRF	0.325		
PRF	0.285	0.720	
FRF	0.140	0.175	0.175

Table 1: RRO between different models with ESBanks as asset.

CorpBond10YAA	MRF	PRF	FRF
MRF	0.345		
PRF	0.315	0.760	
FRF	0.230	0.325	0.330

Table 2: RRO between different models with CorpBond10YAA as asset.

ESIndustrials	MRF	PRF	FRF
MRF	0.605		
PRF	0.425	0.715	
FRF	0.315	0.420	0.440

Table 3: RRO between different models with ESIndustrials as asset.

CorpBond7-10YHY	MRF	PRF	FRF
MRF	0.335		
PRF	0.200	0.465	
FRF	0.185	0.170	0.250

Table 4: RRO between different models with CorpBond7-10YHY as asset.

Overall, we can see that the results are quite similar across assets for the different RROs. Nonetheless, there seem to be one notable exception, as comparing the models estimated for ESIndustrials with other assets show the highest degree of deviation.

In this paper, we cannot determine which threshold from the set of obtained thresholds that stem from the different models is *"the true one"*. As all the regime estimates in general seem to be plausible, we will not tackle this question within this paper. It might be an interesting task for future research, e.g. via Bayesian Model Averaging for the unknown threshold z^*.

5.2 Macroeconomic Risk and the Transmission of Monetary Policy Shocks

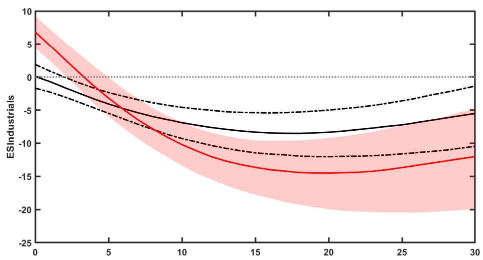
Fig. (11) shows the reaction of our assets in states of high (red area) or (black lines) macroeconomic risk when facing a restrictive one percentage point shock in the short-rate. We see that almost all of our asset variables react as expect: equity of industrial firms falls while corporate bond yields rise. Between the regimes, however, there are notable state-dependent differences for the various asset types. The response of ESIndustrials, Fig. (11 (a)), dies out faster and is (insignificantly) less sensitive to short-rate shocks in the -risk regime. It initially shows a contra-intuitive positive reaction in the high-risk regime that turns negative after about a quarter. The observation that ESIndustrials is (insignificantly) less sensitive to restrictive monetary policy shocks in -risk regimes does not hold anymore in the robustness section. There we find that the impact of short-rate shocks is weaker in high-macro-risk regimes, i.e. in recessions, than in booms. This fits into the literature which finds that MP has er (real) impacts in recession periods, i.e. when our MRF is high[18]. Tenreyro and Thwaites (2016) line out that the impact of monetary policy shocks on real activity is weaker during business cycle downturns. Moreover, Aastveit et al. (2017)find that monetary policy has er effects on the real economy (and inflation dynamics) when various uncertainty measures are elevated. The previously discussed reaction of industrial equity might be one aspect that leads to the their findings. On the contrary, we find that especially risky junk bond yields react to a much larger extend when macroeconomic risk is high.

For ESBanks, Fig. (11 (b)), we can observe quite interesting patterns. Fist, in both regimes the bank index initially reacts positively. Second, the positive reaction is even higher and stays significant for a prolonged period when macroeconomic risk is high. There exists a continuously growing literature that tries to explain this at first sight counter-intuitive finding. In a -yield environment, as it is typical for business cycle downturns in general and longstanding prevailing in the euro area since the European Sovereign Debt Crisis, bank equity seem to benefit from (unexpected) interest hikes. According to Ampudia and Van den Heuvel (2018) bank equity can benefit from unexpected hikes in the policy rates, if they operate within a near-zero interest rate environment. This can be a possible explanation for this at a first glance counter-intuitive finding, as economic slack and a sharp decline with a prolonged period of near-zero policy rates go hand in hand in Europe since the Financial Crisis.

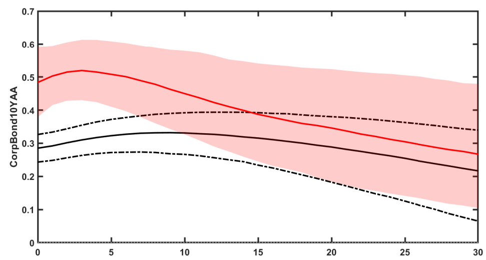
[18]Note that we have inverted this variable in Sect. (3) for ease of interpretation.

Corporate yields, Fig. (11 (c) & (d)), show interesting pattern as well. Bond yields with investment grade face a similar reaction between the states, although the sensitivity is significantly more pronounced in the high-risk state, at least up to the first 8 months after the shock. The high-yield bond yields show a very strong positive reaction in the high-risk state that peaks at around 2.6 percentage points. In contrast to the investment grade bond yields, the high-yield bond yields are affected only on a small scale within a -macro-risk environment. This also fits into the finding of Tenreyro and Thwaites (2016). The authors line out that during recessions, the external finance premium, as it is reflected by the Excess Bond Premium (EBP) in Gilchrist and Zakrajšek (2012), skyrockets and, as a result, amplifies monetary policy shocks. This external finance premium can be assumed to be much larger for risky high-yield bonds than for investment grade bonds. Thus, it would be a good explanation for the respective findings.

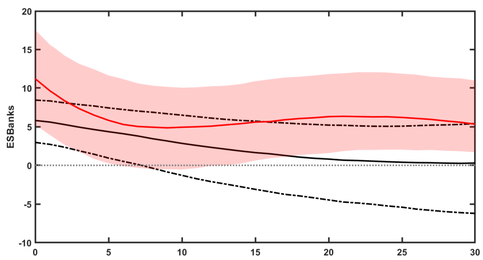
(a) ESIndustrials



(c) AA-rated



(b) ESBanks



(d) High-Yield

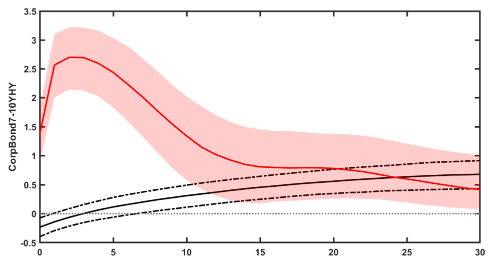


Figure 11: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the MRF.

Notes: median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

5.3 Political Risk and the Transmission of Monetary Policy Shocks

Fig. (12) shows the reaction of assets in states of high or political risk when facing a restrictive one percentage point short-rate shock. In periods of political risk, we see that ESIndustrials, Fig. (12 (a)), experiences a reduction after an initially quite strong, positive reaction. In contrast, ESBanks faces a minor positive reaction that dies out quite fast. We observe a strong positive reaction, namely more than one percentage point, for investment-grade corporate bond yields that abates after about 15 months. On the other side, risky bond yields show no significant reaction in this risk state until abound 15 months after the shock. After that, the reaction is positive.

Turing to the reaction in high-risk regimes we see that equity is in general less sensitive to yield shocks, compared to the -risk regime. This could be an indication that in these high-risk states, asset markets are less attentive to changes in the stance of monetary policy. This interpretation also captures concerns of Benoît Cœré in the introductory statement.

Furthermore, we again see a diverging picture between industrial and financial equity. ESBanks initially reacts positive but turns insignificant after about half-a-year, very counter-intuitive. ESIndustrials experience significant negative reactions after the shock though.

Corporate bond yields face heterogeneous reactions, depending on the rating class. AA-rated bond yields are less impacted in size but abate much ser in a high-risk environment, compared to a -risk regime. One possible driver of this very pronounced state-dependency with respect to political risk within high-grade corporate bonds might be rooted in the substitutability between them and government bonds. During risky political times, investors might evade holding government bonds and increase their high-grade corporate bond holdings. The resulting increased demand might er the susceptibility of their yields to monetary policy surprises.

Non-investment-grade corporate bond yields do not show this pronounced state-dependency. Although a significant positive reaction occurs earlier and abates faster in the high-risk regime, both kinds of yields react very similar across both high- and -risk regimes, for the horizon under consideration.

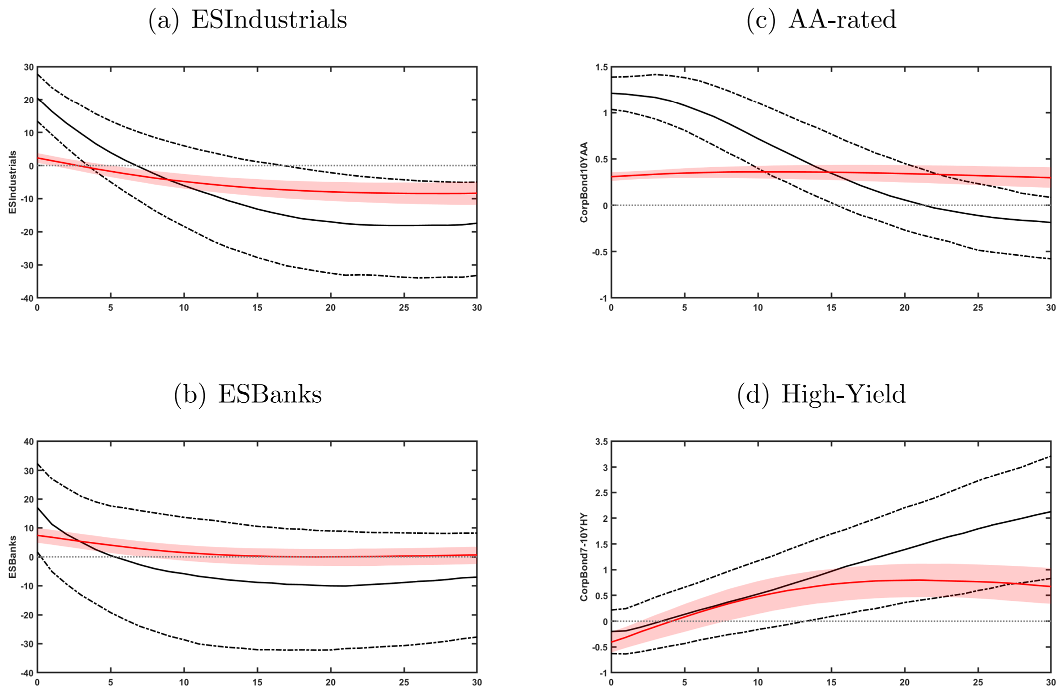


Figure 12: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the PRF.

Notes: median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

5.4 Financial Market Risk and the Transmission of Monetary Policy Shocks

When taking a look at the reaction of our assets to a restrictive short-rate shock in regimes of high and financial risk, Fig. (13), we again see very diverging pictures between high-risk or -risk states. Both distinct types of equity show positive reactions in the high-risk regime, which are very pronounced for ESBanks.

Interestingly, while ESIndustrials turns significantly negative after about 10 months, the median reaction of ESBanks stays positive over the whole horizon of 30 months. One possible explanation for this outstandingly different reaction of financial equity might be linked to the role of expected increased bank margins if a restrictive monetary policy shock occurs in a prolonged period of interest rates. Recall that the high-risk regimes for our model with ESBanks, as depicted in Fig. (7), concentrate around the Financial Crisis, the European Government Debt Crisis and around the year 2016. As outlined in e.g. Hayo et al. (2018) or Claessens et al. (2018), bank margins deteriorate in long lasting interest rate environments, which in turn diminishes their (expected) profitability and, as a consequence, the value of their equity. The prospect of higher net margins in their core business backs up their firm value.

For corporate bonds the picture is twofold: while investment-grade bond yields react similar, independent of the regime, high-yielding bond interest rates are strongly negatively impacted, more than one percentage point, in the first six months after the shock in a high-risk regime. However, the sign of the reaction changes in a hump-shaped manner, resulting in a peak reaction of two percentage points after about one and a half years. There exist some possible explanations for this curios pattern. On the one hand a restrictive short-rate shock can be interpreted as a signal for more sound environment that leads to an immediate downward adjustment of risk premia. On the other hand, restrictive monetary policy increases future default probabilities via its dampening effect on the economy. This nexus can be expected to be strongest for less sound firms. The presented results fit the narrative of Rüth (2017), who finds that the transmission of monetary policy is stronger during periods of high financial stress for the US. Using a local projection framework to elaborate effects of monetary policy shocks on economic activity and financial variables, the author measures financial stress with the EBP of Gilchrist and Zakrajšek (2012) which in turn is high for non-investment grade corporate bonds.

(a) ESIndustrials

(c) AA-rated

(b) ESBanks

(d) High-Yield

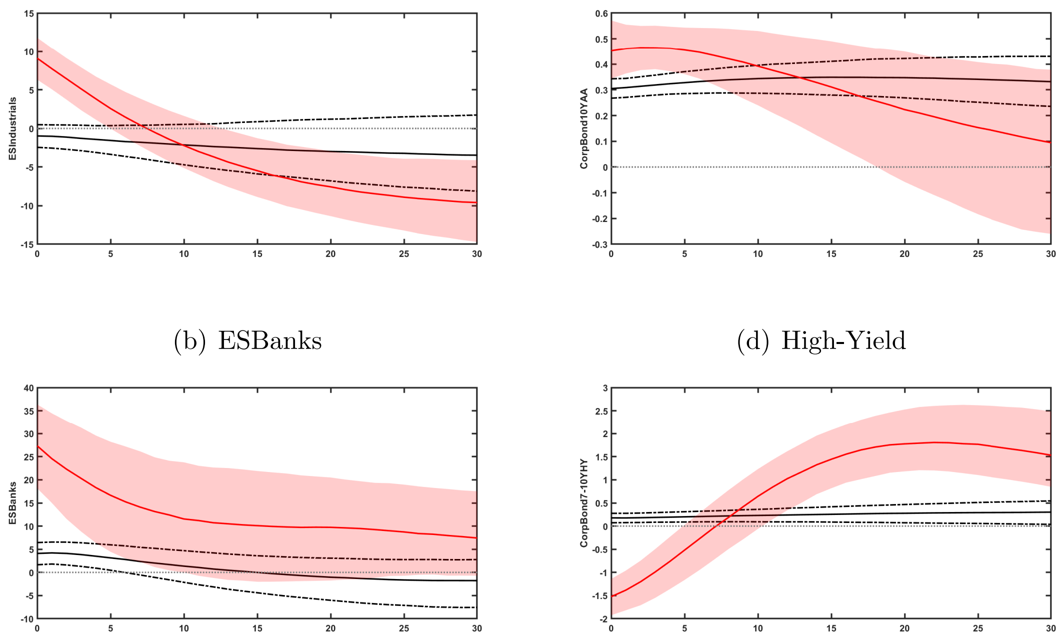


Figure 13: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the FRF.

Notes: median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

6 Sensitivity Analysis

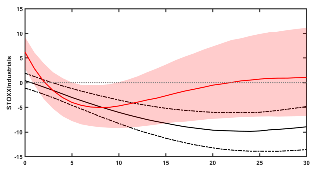
The results of the previous section undergo a variety of robustness checks. We use alternative assets, broad European indices such as STOXXBanks and STOXXIndustrials, as well as other corporate bond yields (BBB, the er bound of investment-grade classification, also with 10-year maturity). Additionally, we incorporate an alternative shadow interest rate provided by Wu and Xia (2016). The qualitative findings discussed before hold in almost all cases.
Further on, we test for two alternative orderings to identify the short-rate shock. Therefore, we change the assumed contemporaneous relationships among the model variables. Again, the results remain qualitatively unchanged, although the size or significance of our findings even increase in some cases.
Since the results are very similar, we do not present the respective regimes for the various models and their overlapping properties. Instead, we focus on impulse response functions. Nevertheless, the results are available on request.

6.1 Alternative Model Variables

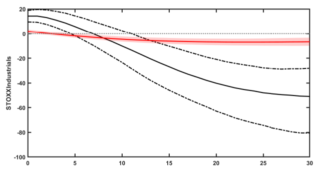
Equity Indices

While we focus on equity indices that list only firms of euro area member states in the main section, we also use two broader European indices, namely STOXXBanks and STOXXIndustrials, because these broad indices can also be assumed to primarily be driven by the euro area, as it represents by far the largest share of the European economy. Fig. (14) contains the reaction of STOXXIndustrials for our three distinct threshold variables and displays strong state-dependency. As we can see, the findings do not differ qualitatively, whether we use the shadow rate provided by Krippner or by Wu and Xia (2016). Equity of European industrial firms is, in general, affected negatively in the long-term perspective and is less sensitive to monetary policy surprises when we are in high-macroeconomic or -political risk regimes. One exception is the state of high financial risk in which we can observe a positive reaction that turns insignificant after one or four months, depending on the model.

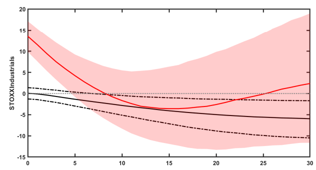
(a) Threshold variable is the MRF



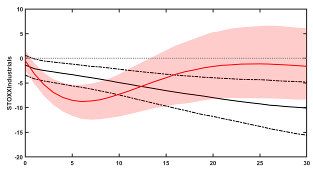
(c) Threshold variable is the PRF



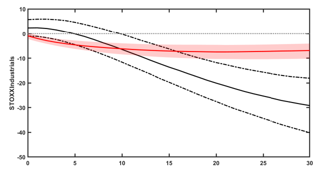
(e) Threshold variable is the FRF



(b) Threshold variable is the MRF



(d) Threshold variable is the PRF



(f) Threshold variable is the FRF

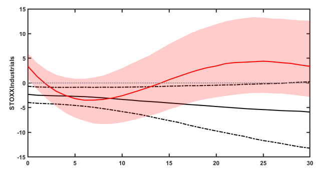


Figure 14: Impulse response functions of STOXXIndustrials to a one percentage point shock in the short-rate. The upper row stems from models estimated with Krippner Shadow Rate, the bottom row stems from models with Wu and Xia (2016) Shadow Rate.

Notes: median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

In Fig. (15) we can see the reaction of STOXXBanks for models with various threshold variables and two distinct shadow rates. In these setups, we can also, in general, find the curios pattern of a positive reaction of bank equity during high-risk regimes. This finding is most pronounced when our threshold variable is financial risk. Again, we have one exception: the model with the Wu and Xia (2016) shadow rate, (Fig. 15, (b)), where the surprising and contra-intuitive positive reaction is higher in the regime of macroeconomic risk.

(a) Threshold variable is the MRF

(c) Threshold variable is the PRF

(e) Threshold variable is the FRF

(b) Threshold variable is the MRF

(d) Threshold variable is the PRF

(f) Threshold variable is the FRF

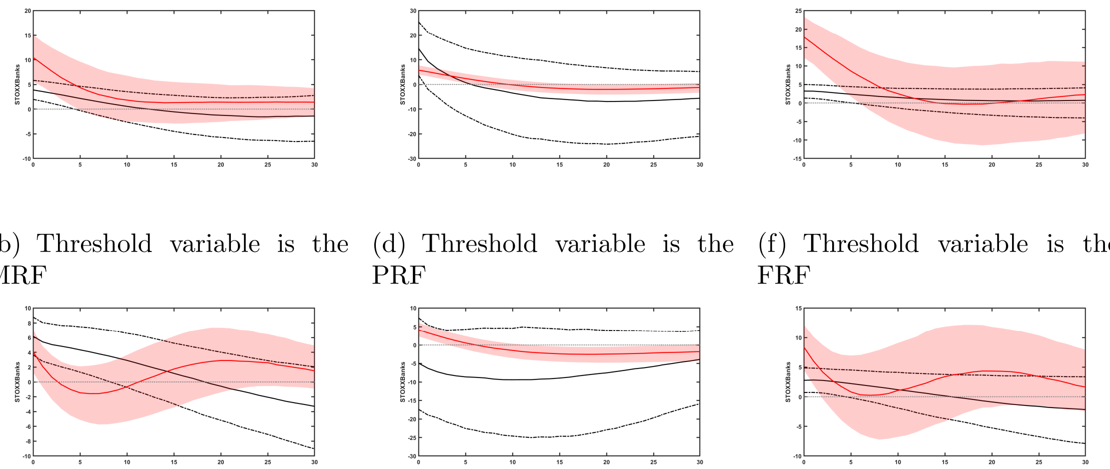


Figure 15: Impulse response functions of STOXXBanks to a one percentage point shock in the short-rate. The upper row stems from models estimated with Krippner Shadow Rate, the bottom row stems from models with Wu and Xia (2016) Shadow Rate.

Notes: median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

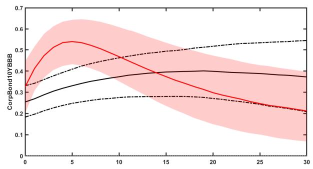
Corporate Bond Yields

While in the main part we explicitly distinguish between the yield of the highest (available) investment-grade bonds, AA-rated, and non-investment-grade high-yield bonds, we now take a closer look on a rating class that marks the er end of investment-grade and, thus, lies in between the former two: BBB-rated corporate bond yields with 10-year maturity.

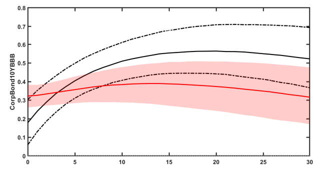
Fig.(16) contains the respective impulse response functions. If macroeconomic risk is our threshold variable, we se notable differences across the two regimes. The pattern looks like a mixture of those presented in Fig. (11, (c) & (d)). For the other two threshold variables we find no outstanding state-dependency. If we use political risk as threshold variable, the reaction looks more like the reaction of the high-yield bond yield, depicted in Fig. (12, (d)), although BBB is still investment grade. The opposite holds for the models when financial risk is the threshold. There, the reaction looks more like the behavior of the AA-rated bond yield, see Fig. (13, (c)).

From these additional results we can conclude that there is a gradual shift in relevance of different types of risk for different rating classes. The riskier the underlying bond, the more we see pronounced state-dependency with respect to macroeconomic risk. The better the respective rating of a bond, the more we find political-risk-related state-dependency. For financial risk, the shift is a sharp one: as long as the underlying bond remains investment-grade, we only see minor differences of the yield reaction to short-rate shocks across the states. This changes drastically for non-investment grade bonds. There, we find very pronounced state-dependency with respect to financial risk.

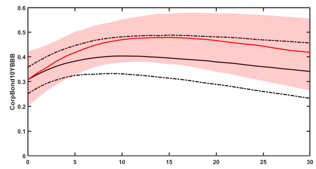
(a) Threshold variable is the MRF



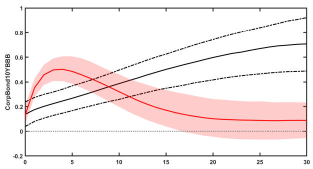
(c) Threshold variable is the PRF



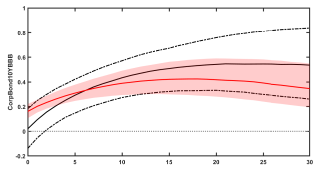
(e) Threshold variable is the FRF



(b) Threshold variable is the MRF



(d) Threshold variable is the PRF



(f) Threshold variable is the FRF

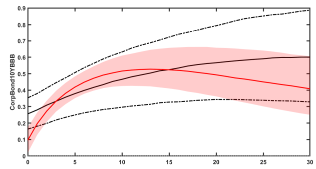


Figure 16: Impulse response functions of BBB Corporate Bond 10-year yield to a one percentage point shock in the short-rate. The upper row stems from models estimated with Krippner Shadow Rate, the bottom row stems from models with Wu and Xia (2016) Shadow Rate.

Notes: median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

6.2 Alternative Orderings

In this section, we present results that stem from models identified with an alternative ordering of our model variables. Hence, we distinguish within this section between two different ways of arranging our variables in Y_t.

$$\text{Order 2: } Y_t = [MRF_t \ FRF_t \ SR_t \ PRF_t \ asset_{i;t}]'. \tag{15}$$

The motivation of order 2 is similar to the one presented in the main part, but reflects the possibility that the ECB does not only contemporaneously take into account the (most inert) macroeconomic circumstances reflected by our MRF, but also financial market risk, captured by our FRF. This can be justified by maintaining a sound transmission of ECB's monetary policy through the financial system. Thus, we order the short-rate behind these two variables. Additionally, we assume that political risk, PRF, is impacted by MRF, FRF, and short-rates within the same

period. Assets are, again, ordered last.
The second alternative ordering to reflect contemporaneous interdependences between the variables is order 3:

$$\text{Order 3: } Y_t = [MRF_t\ FRF_t\ PRF_t\ SR_t\ asset_{i;t}]'. \tag{16}$$

With this assumed arrangement of variables, some additional considerations go in hand. While the contemporaneous relationship between short-rates, macroeconomic and financial risk remain unchanged, we also imply with ordering the political risk factor before the short-rate that it is also affected by political shocks within the same period. This seems to be a quite harsh assumption because it implies that policy rates might also be driven by political distortions. According to the mandate of the ECB, accounting for these distortions is not a key subject. It states that the ECB has to focus on inflation and real activity and, should the situation arise, to maintain working transmission mechanisms. Nevertheless, we Assets are again ordered last to be impacted by all other variables within the same period.
In the foling we present and briefly discuss the results stemming from these alternatives. They remain qualitatively unchanged in almost all cases.

Macroeconomic Risk and Transmission of Monetary Policy Shocks

Fig. (21) and Fig. (18) show the reaction of our assets discussed in Sect. (5) for the two alternative orders described above for the case when macroeconomic risk is the threshold variable. Again, the shock is a one percentage point increase in the (shadow) short-rate. All assets, except ESIndustrials, show the same qualitative behaviour in both alternatives. ESIndustrials, on the other side, reacts less strongly during stages of increased macroeconomic risk when focusing on a longer horizon.

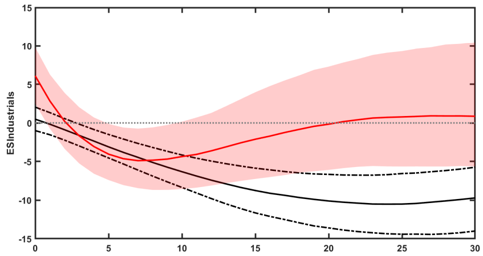
Political Risk and Transmission of Monetary Policy Shocks

Fig. (19) and Fig. (20) contain the reaction functions of the respective assets to a 1 percentage point interest rate shock, identified either by order 2 or 3, for political risk as threshold variable. Again, the results are very similar to our main part, except that bank equity shows a negative reaction in the model identified with order 3.

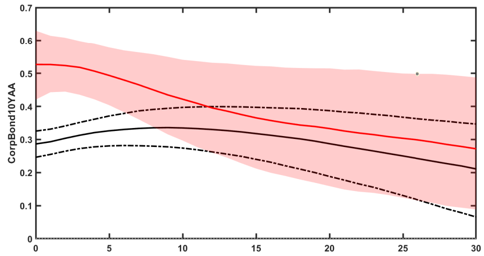
Financial Risk and Transmission of Monetary Policy Shocks

The reaction of our assets, conditional that financial risk is the threshold variable and that we apply order 2 or 3, respectively, is captured in Fig. (21) and Fig. (22). In both ordering schemes, we see an outstanding positive effect of short-rate hikes on

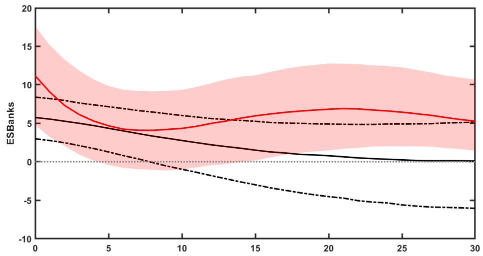
(a) ESIndustrials



(c) AA-rated



(b) ESBanks



(d) High-Yield

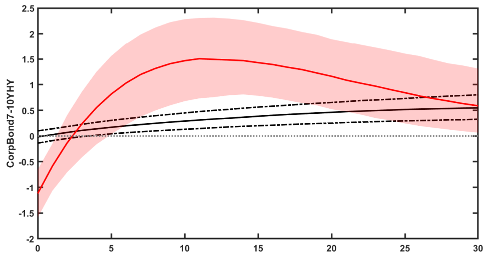
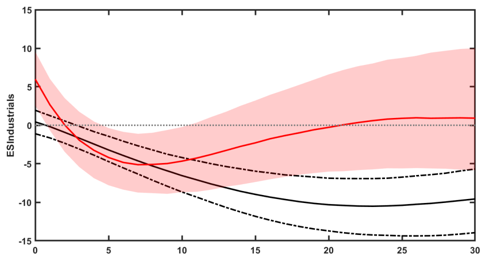
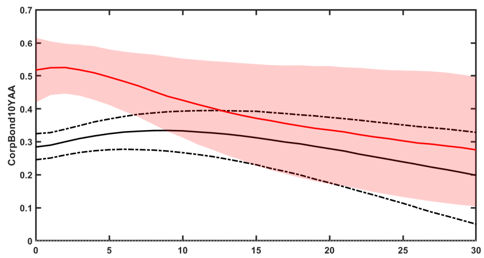


Figure 17: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the MRF, identification obtained from order 2. *Notes:* median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

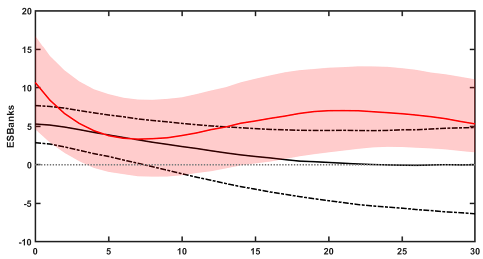
(a) ESIndustrials



(c) AA-rated



(b) ESBanks



(d) High-Yield

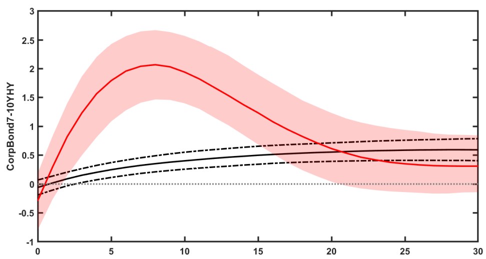


Figure 18: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the MRF, identification obtained from order 3. *Notes:* median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

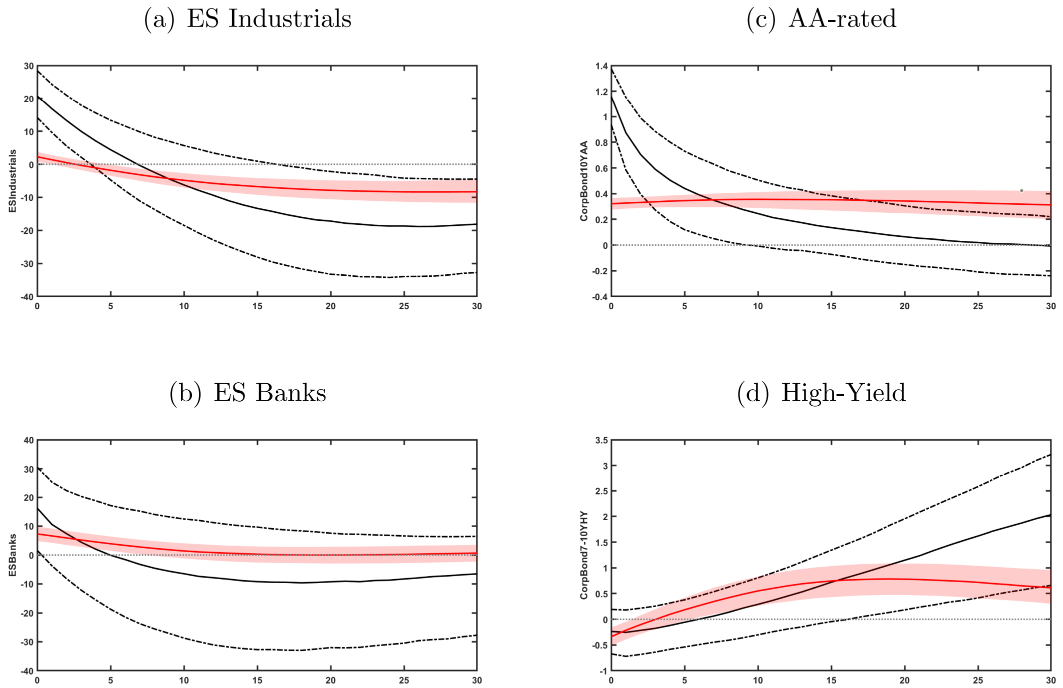


Figure 19: Impulse response functions of assets to a 1 percentage point shock in the short-rate, threshold variable is the PRF, identification obtained from order 2.
Notes: median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

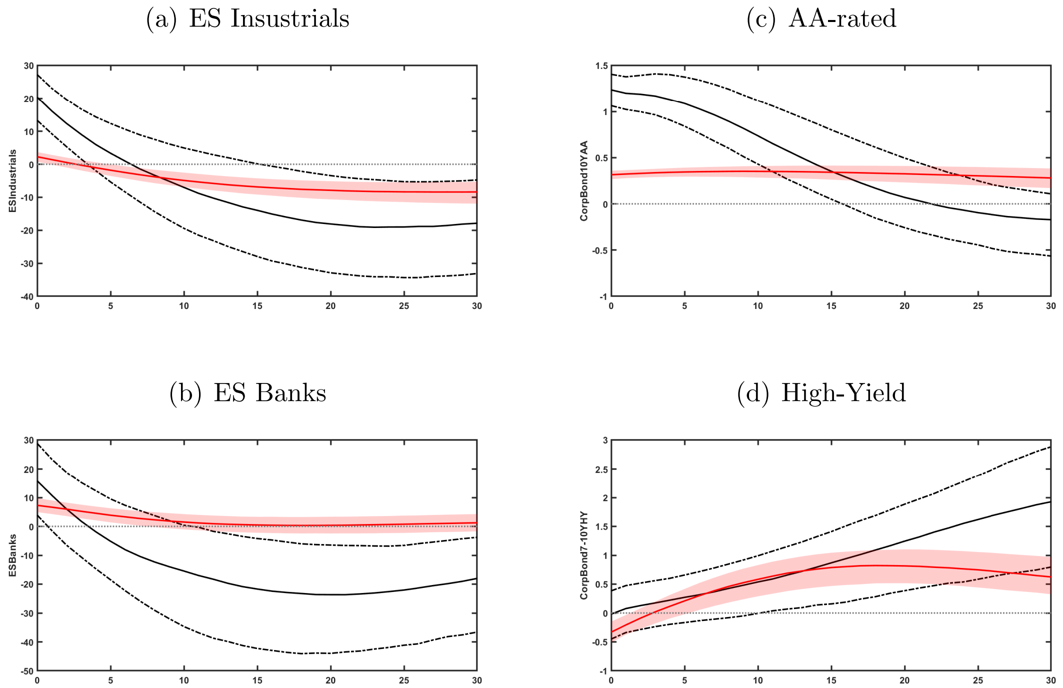


Figure 20: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the PRF, identification obtained from order 3.
Notes: median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

equity during regimes of high financial risk. Again, bank stocks show the surprising positive reaction even during periods of financial tension. While investment-grade bond yields are impacted quite similar, we obviously see divergent pattern for -grade bond yields.

7 Summary and Conclusion

Within the transmission mechanisms of monetary policy, the value of assets plays an important role. Asset pricing theories emphasize the critical role of discount rates to evaluate assets. The (perceived) risk of market participants is crucial for them. The riskier the asset, the higher is the respective discount rate.

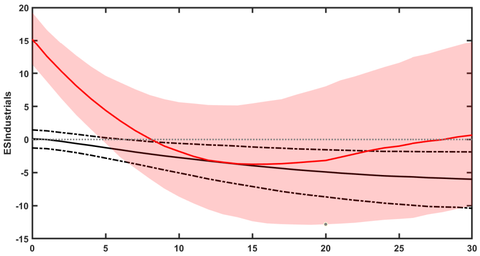
These rates reflect, among other things, a set of different risks. Depending on the respective asset, some of these risks are considered to be more relevant than others. As a consequence, asset pricing has a strong nexus with distinct risks. In a first step, we extract three different risk factors of the euro area via principal component analysis: a factor closely related to the business cycle, namely the macroeconomic risk factor, a factor that tracks economic policy uncertainty, namely the political risk factor, and a factor that captures financial tensions and turmoils, namely the financial risk factor. The extracted factors fit the course of the major European Crises and are similar to alternative suggestions of risk measures made by the literature.

One key problem is that various types of risk interact with each other, especially during severe crises periods. This motivates the usage of vectorautoregressions as well as the incorporation of state-dependency, i.e. high- or -risk regimes. Nevertheless, we emphasize the caveat of "correct" risk delimitation and illustrate how the indicated regimes overlap for the sets of estimated TVAR-models.

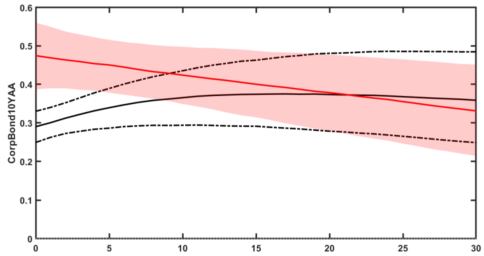
Analyzing the state-dependent sensitivity of asset prices to a short-rate shock, the impulse responses show that asset prices are disparately susceptible in different risk environments. We have state-dependent reactions of asset prices to shocks in the short-rate.

We can summarize these differences in susceptibility: when we distinguish between high and macroeconomic risk, in general we find that equity of industrial firms is impacted negatively in both risk states and, depending on the model setup and variable selection, is in most cases less sensitive during states of high macroeconomic risk, i.e. during recessions. For financial equity, within this paper we focus on banks, we either find non-significant or even positive reactions when confronted with restrictive monetary policy shocks. The at first glance very counter-intuitive, often

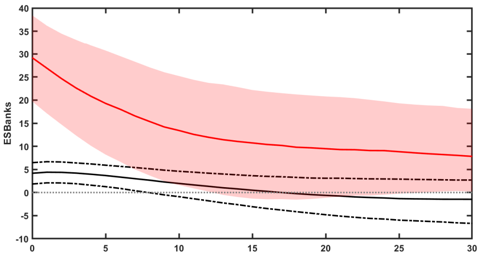
(a) ES Industrials



(c) AA-rated



(b) ES Banks



(d) High-Yield

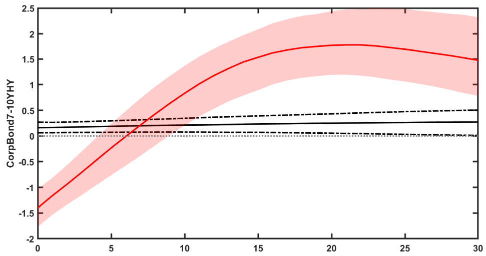
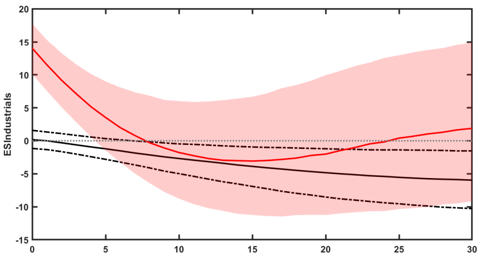
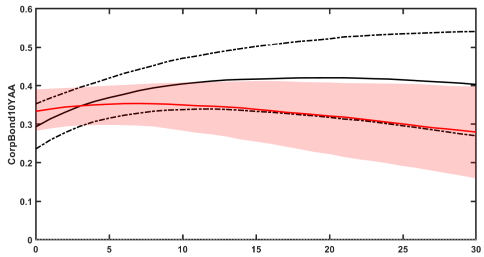


Figure 21: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the FRF, identification obtained from order 2. *Notes:* median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

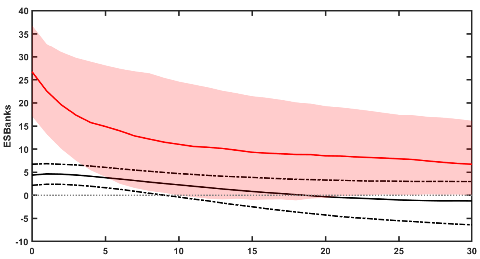
(a) ES Industrials



(c) AA-rated



(b) ES Banks



(d) High-Yield

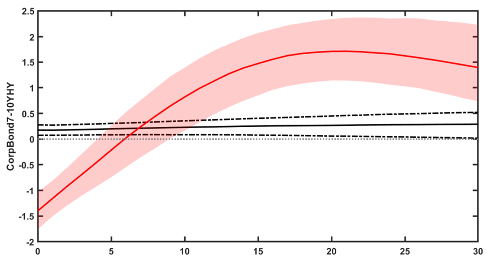


Figure 22: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the FRF, identification obtained from order 3. *Notes:* median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red shaded) and low-risk regimes (black lines).

significant positive reactions occur primarily during phases of elevated macroeconomic and financial risk. For non-investment-grade corporate bond yields, we find that their sensitivity with respect to short-rate shocks is highest in periods of elevated macroeconomic risk. AA-rated corporate bonds show the largest divergence across regimes, if we distinguish between high and political risk.

From these results, we can conclude for corporate bond yields that there is a gradual shift in relevance of different types of risk that depends on the respective rating. The riskier the underlying bond, the more we see pronounced state-dependency with respect to macroeconomic risk. The higher the respective rating of a bond, the more we find political-risk-related state-dependency. For financial risk, the shift is a sharp one: as long as the underlying bond remains investment-grade, we only see minor differences of the yield reaction to short-rate shocks across the states. This changes drastically for non-investment grade bonds. There, we find very pronounced state-dependency with respect to financial risk.

Addressing the concerns uttered in the introduction, in the end we have to take a differentiated look at the respective kind of asset in combination with the currently prevailing risk regime. For policy makers, the findings implicate that the transmission of monetary policy via asset markets is quite heterogeneous and highly depends on the respective risk-regime. The implications for investors are quite strong: the timing, or, more specifically, the prevailing risk environment, determines the intensity and in some cases even the sign of asset price adjustments.

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Appendix

Data

Variable	Transformation	Source	Identifier
EA Index of Industrial Production (excl. construction, sa, wda)	YoY growth rate	Datastream	EKIPTOT.G
EA Consumer Price Index (wda, sa)	YoY growth rate	Datastream	EMEBCPALE
Unemployment, in % (wda, sa)	none	Datastream	EKESUNEMO
Hours Worked, quarterly, in Mill. hours (wda, sa, Chow-Lin-interpolated)	YoY growth rate	Datastream	EKEBEHWEO
Term Spread, in % (10Y - 3M GerGovBond)	none	Datastream, Authors' calculations	TRBD10T TRBD3MT
€Coin Indicator	none	CEPR	HLink
VDAX	ln*100	Datastream	VDAXNEW
Business Climate Index (sa, not wda)	none	European Commission	[ei_bsci_m_r2]
Industry: New Orders, quarterly (sa, not wda, Chow-Lin-interpolated)	none	European Commission	[ei_bsin_q_r2]
Industry: Capacity Utilization, quarterly (sa, not wda, Chow-Lin-interpolated)	none	European Commission	[ei_bsin_q_r2]
Consumer Climate: FinSit12M (sa, not wda)	none	European Commission	[ei_bsco_m]
Consumer Climate: EconSit12M (sa, not wda)	non	European Commission	[ei_bsco_m]
Consumer Climate: Trust (sa, not wda)	none	European Commission	[ei_bsco_m]

Table 5: List of variables, their initial transformation, and source, that are assumed to be primarily driven by the present business cycle and expectations about future real activity.

Variable	Transformation	Source	Identifier
EA News-Based Policy Uncertainty Index	none	Baker et al. (2016), Authors' calculations	-
Spread EA - GER, in %	none	Datastream, Authors Calculations	Debt: ITESC3F2,FRCGVTPA,ESESC3F2, PTCGDEBT,GREXDGOVA,IREXDGOVA 10YGovYields: ITOIR080R,FROIR080R, ESOIR080R,PTOIR080R,GROIR080R, IROIR080R,BDMIR080R
SovCISS	none	ECB	CISS.M.U2.Z0Z.4F.EC.SOV_EW.IDX

Table 6: List of variables, their initial transformation, and source, that are assumed to be primarily driven by (economic) policy risk.

Variable	Transformation	Source	Identifier
CISS-Subindex StockMarkets	none	Datastream	EMCIEMN
CISS-Subindex InterBanks	none	Datastream	EMCIFIN
CISS-Subindex MoneyMarket	none	Datastream	EMECM3E
ECB MMM, in €Mill	ln*100	Datastream, Author's Calculations	EMLDEPO,EMEBSMLFA, EMECAEX,EMAREFO
Ted-Spread, in %	none	Datastream, Author's calculations	TRBD3MT,EIBOR3M

Table 7: Variables assumed to be driven primarily by financial market risk, their transformation, and respective source with the specific identifier.

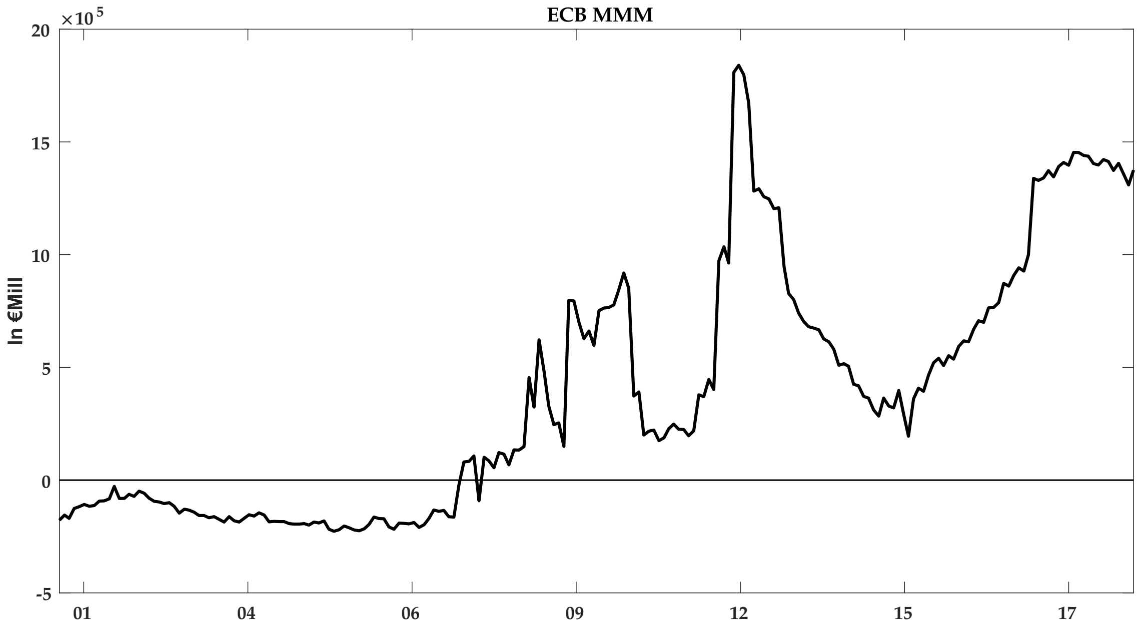

Figure 23: Quantitative measure for ECB's programs that are directed towards money market distortions and liquidity provision.

Principal Component Analysis

Eigenvalues				
No. of Eigenvalue	Value	Proportion	Cum. Proportion	
1	7.1770	0.5521	0.5521	
2	2.0777	0.1598	0.7119	
3*	1.5025	0.1156	0.8275	
⋮	⋮	⋮	⋮	
13	≈ 0	< 0.01	1.0000	
Loadings				
Variable	PC1	PC2	PC3	··· PC13
Industrial Production	0.2972	0.0058	0.3550	
CPI	0.0332	-0.5741	0.2502	
Unemployment	-0.1463	0.3890	0.3818	
Hours Worked	0.3421	-0.1709	-0.0730	
Term Spread	-0.2063	0.3131	0.2477	
€Coin Indicator	0.3190	0.1640	0.1609	
Business Climate Index	0.3418	-0.1187	0.1929	
VDAX	-0.2022	-0.1574	-0.3792	
New Orders, Industry	0.2940	0.1044	0.2915	
Cap. Ut., Industry	0.6267	-0.3580	-0.0414	
Cons. Clim., FinSit12M	0.2684	0.2343	-0.4301	
Cons. Clim., EconSit12M	0.3223	0.2998	-0.1276	
Cons. Clim., Trust	0.3176	0.2056	-0.3226	

Table 8: Principal Component Analysis for the set of variables assigned to macroeconomic risk.

Notes: the asterisk indicates the number of factors that optimally solve the trade-off between sparse number of factors and best explanation of covariance among the variables.

Eigenvalues			
No. of Eigenvalue	Value	Proportion	Cum. Proportion
1*	1.8580	0.6193	0.6193
2	0.7551	0.2517	0.8711
3	0.3868	0.1289	1.0000
Loadings			
Variable	PC1	PC2	PC3
SovCISS	0.4727	0.8788	0.0657
EA NBPUI	0.6267	-0.2847	-0.722821
Spread EA - GER	0.6165	-0.3831	0.6879

Table 9: Principal Component Analysis for the set of variables assigned to political risk.

Notes: the asterisk indicates the number of factors that optimally solve the trade-off between sparse number of factors and best explanation of covariance among the variables.

Eigenvalues

No. of Eigenvalue	Value	Proportion	Cum. Proportion
1	3.0775	0.6155	0.6155
2*	1.1335	0.2267	0.8422
3	0.4891	0.0978	0.9400
⋮	⋮	⋮	⋮
5	≈ 0.1	0.0174	1.0000

Loadings

Variable	PC1	PC2	PC3	⋯	PC5
CISS-Sub StockMarkets	0.4809	-0.3171	0.5013		
CISS-Sub InterBanks	0.5439	-0.0637	0.2392		
CISS-Sub MoneyMarkets	0.4809	-0.317071	0.5013		
ECB MMM	0.1057	0.8752	0.4324		
Ted-Spread	0.4409	0.3429	-0.6704		

Table 10: Principal Component Analysis for the set of variables assigned to financial risk.

Notes: the asterisk indicates the number of factors that optimally solve the trade-off between sparse number of factors and best explanation of covariance among the variables.

High-risk Regime Overlap

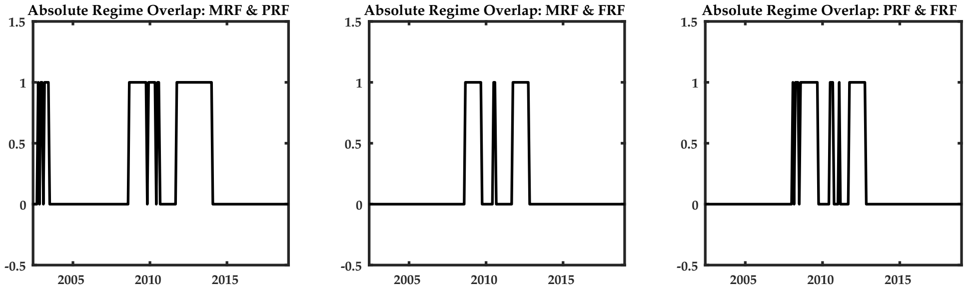

Figure 24: TVAR-models with ESBanks.
Notes: black-solid is the high-risk regime overlap between MRF & PRF (left), MRF & FRF (middle), and PRF & FRF (right).

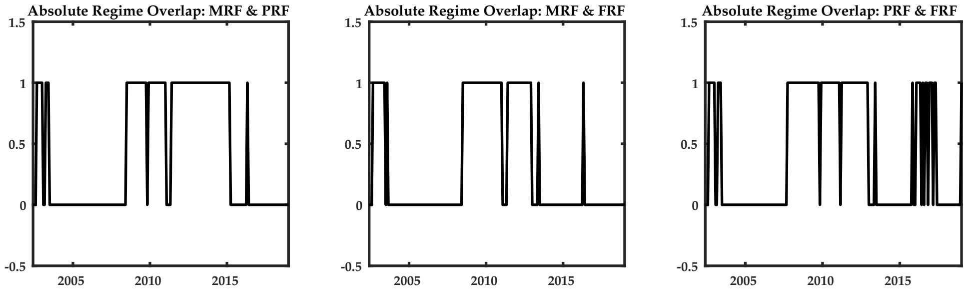

Figure 25: TVAR-models with ESIndustrials.
Notes: black-solid is the high-risk regime overlap between MRF & PRF (left), MRF & FRF (middle), and PRF & FRF (right).

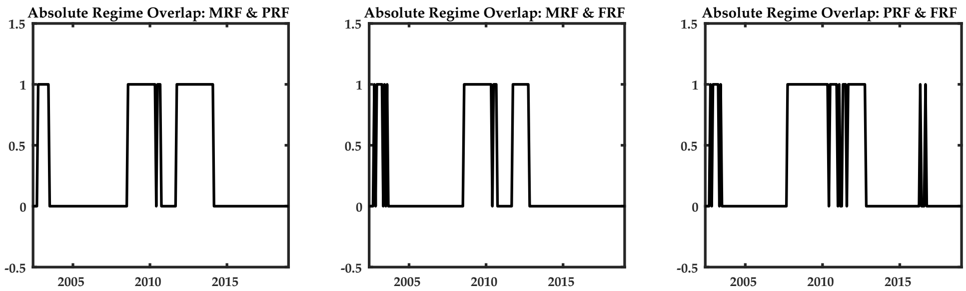

Figure 26: TVAR-models with CorpBond10YAA.
Notes: black-solid is the high-risk regime overlap between MRF & PRF (left), MRF & FRF (middle), and PRF & FRF (right).

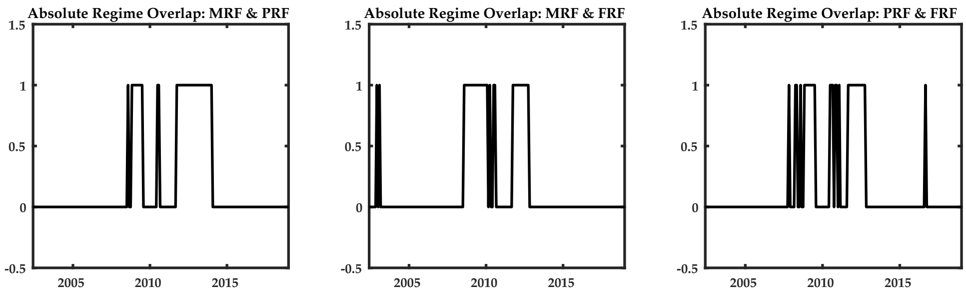

Figure 27: TVAR-models with CorpBond7-10YHY.
Notes: black-solid is the high-risk regime overlap between MRF & PRF (left), MRF & FRF (middle), and PRF & FRF (right).

Smooth Transition: Financial Risk

An alternative way to construct state-dependency and the respective transition across the states within a VAR-framework are transition functions. We construct a standard logistic transition function, $G(z_t, \gamma, c)$, reflected in Eq. (17). It is determined by its input values z_t, the transition parameter γ, and a shift parameter c. With this function, the determination of a state is not binary anymore:

$$G_t(z_t) = \frac{1}{1 + \exp(-\gamma(z_t - c))}, \quad G_t \in (0, 1) \tag{17}$$

For our analysis, z_t equals FRF_t. The transition properties of $G(.)$, i.e. how violently the model switches across regimes, depends on the choice of γ. For $\gamma \rightarrow \infty$, we are back in a binary setup, as the transition across states is very sharp, limiting the value space of $G(.)$ on 0 or 1, depending on passing the shift parameter c. In contrast, for $\gamma \rightarrow 0$ we have no transition at all as G approaches 0.5 for all values of FRF.

To determine this crucial parameter, we combine the ideas of Auerbach and Gorodnichenko (2012) with the varying outcomes of the set of estimated models in our main section. The authors' idea is to match the properties of their transition function with the data they observe. As they are interest in asymmetries across recessionary or non-recessionary stages of the business cycle with respect to fiscal policy, the standardized 7-quarter moving average GDP-growth of the US is their variable that determines the transition of their model, z_t. As it has zero-mean and unit-variance, they set $c = 0$. They observe that the US is on average in about 20 per cent of their sample in a recession. Additionally, they assume that the economy is in recession if $G(.) > 0.8$. This results in $\gamma = 1.5$ such that $Pr(G(z_t, \gamma, c) > 0.8) = 0.2$ holds. We proceed in a similar way to determine two alternative transition functions. In a first step, we need to know how much of our sample is characterized by high- or -risk regimes. As there exits no universally acknowledged indicator that clearly states when the euro area is in a high or financial risk state, we use the set of regime estimates from the main section, see Tab. (1) to Tab (4), right corners, or Fig. (7) to Fig. (10), right columns, and average over them. We find that we are in a high-risk regime in about 30% of the sample. We deviate from the ad hoc assumption of Auerbach and Gorodnichenko (2012) and assume that we are in a high financial risk regime if $G(.) > 0.7$, such that $Pr(G(z_t, \gamma, c) > 0.7) = 0.3$. Otherwise, our transition function would primarily be driven by the events during the Financial Crisis and the European Government Debt Crisis. Thus, it would not take into account the uncertainty about the risk state at the end of our sample, which motivates the

alternative modeling of states via smooth transition functions.
First, we distinguish between two approaches to determine γ. The first one assumes that the shift parameter c is zero, as our variable that determines the transition, FRF, has zero mean and unit variance, like the one in Auerbach and Gorodnichenko (2012). This yields $\gamma = 3.1$ to satisfy the condition that $Pr(G(z_t, \gamma = 3.1, c = 0) > 0.7) = 0.3$. Alternatively, if we set $c = 0.28$, which is the average of the estimated threshold of the four different models with FRF as threshold variable, we obtain $\gamma = 1.9$ such that $Pr(G(z_t, \gamma = 1.9, c = 0.28) > 0.7) = 0.3$ holds. Fig. (28) displays these two slightly different transition functions.

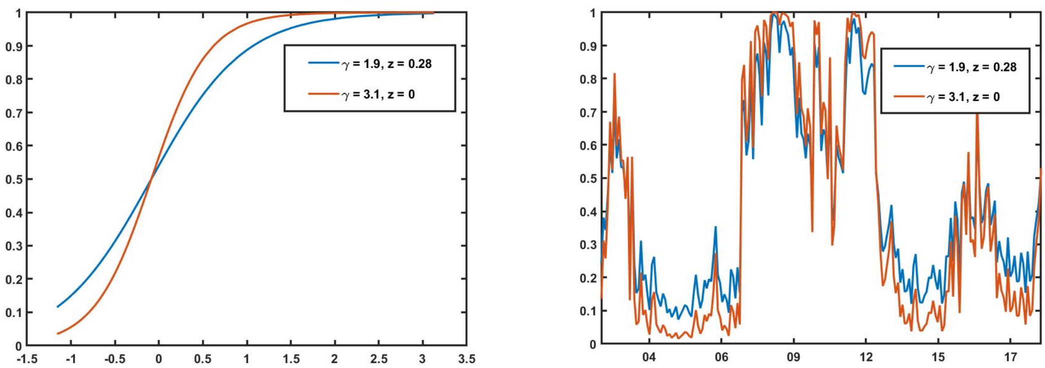

Figure 28: The left figure shows the transition functions $G(FRF, \gamma, z)$. The right figure shows the value of the transition functions $G_t(FRF_t, \gamma, z)$, for given γ and z, respectively, over our sample.

We can see that both transition functions are very similar and show the same dynamics as our various binary state-determining functions from the main section. They peak during the Financial Crisis and, to a smaller extent, during the European Government Debt Crisis. Similar to the binary indicator functions of the main section, depicted in Fig. (24) to Fig. (27), the fluctuation of these continuous transition functions are very high around the same period at the end of our sample. This emphasizes that there lurk pitfalls when assessing the degree of financial risk inherent in the euro area around this period. Financial risk is elevated but by far less than during the Financial Crisis. Thus, the binary indication of financial risk in the main section should be taken with a grain of salt during 2015 to 2017.