ABOUT THE LINK OF MONETARY POLICY TO HOUSEHOLD DEBT, RISK IN THE FINANCIAL SYSTEM, AND INEQUALITY

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Doctoral Thesis

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Preface

During the last two decades, macroeconomics in general and monetary economics in particular have been shaped by the consequences and implications of crises. The outstandingly deep recession in 2008, that followed a financial meltdown in the Western hemisphere, had severe impacts all around the globe. These crises urged both fiscal and monetary authorities to counteract the immense financial and macroeconomic stress. They aimed at calming down markets, often with the intention to prevent even deeper turmoil. The crises and the corresponding measures that have been conducted since then are often characterized by their extraordinary nature. Consequently, they shaped the discussion about the role central banks played, play, and have to play in economics. These discussions focus on direct impacts and the effectiveness of monetary policy, but also on its implications for and possible side effects on a plethora of areas.

Hence, this doctoral thesis picks up three distinct fields that currently are of particular interest for central bankers and politicians. The first field deals with the role monetary policy plays for private sector debt. High levels of debt in the run-up to the Financial Crisis, together with their respective securitization, were key elements to trigger severe financial disruptions. Illuminating possible changes in the interaction between debt, economic activity, and monetary policy can help to better understand the mechanisms involved in transmitting monetary policy. Furthermore, we can address the questions, if monetary policy has contributed to the built-up of household debt and if monetary policy is an appropriate tool to reduce it.
The second field deals with the phenomenon of risk within the financial system. As banks from all over the world were involved in US mortgage and securitization markets, these banks loaded risks onto their balance sheets up to an inappropriate level. They did so either indirectly, via trusting the probably too optimistic ratings of securities, or directly, by granting credit to borrowers who lack creditworthiness. Thus, the risk-taking behavior of financial intermediaries needs to be unveiled and evaluated, especially in the context of the effects that monetary policy has on it.
Furthermore, engaging in risky investments occurs in asset markets, too. Prices of

assets are in general subject to a vast spectrum of different risks. These risks need to be measured and their interactions with each other as well as their effects on asset markets in the context of monetary policy have to be assessed. The possibly diverging sensitivity of various asset prices to monetary policy shocks, conditional on a particular risk-state, bears the danger that investors are caught off guard when e.g. short-rates face unexpected adjustments. In addition, policy makers have to be aware of potential asymmetric reactions of asset prices to their policy decisions, as they are an important element of transmission for monetary policy.
The observed surge of asset prices during the recent years leads to the third field this thesis picks up: monetary policy and its distributional consequences. On the one side, the very accommodative monetary policy has gone in hand with an enormous surge in asset prices in almost all countries of the Western hemisphere. On the other side, yields have fallen tremendously for all investment horizons and seem to remain "low for long". These aspects are possibly accompanied by the stimulating effect of looser monetary policy on economic activity, especially employment. Thus, there is a vivid debate about the impacts of monetary policy on the distribution of wealth and income: 'cui bono?' As different countries have disparate tax systems and redistribution approaches, the effects monetary policy has on the distribution of national incomes might be notably different.

This thesis tackles the outlined issues with four different papers. They are briefly lined out in the following.

The first paper studies the nexus between monetary policy, private non-financial sector indebtedness, and the real economy for the US. It focuses on the role monetary policy plays for household debt, in particular residential mortgage debt. Using time-varying-parameter vector-autoregressions, we uncover that monetary policy shocks, in general, have become less effective over time. The decline in sensitivity to shocks in short-rates is very pronounced for mortgage debt. A dynamic-stochastic-general-equilibrium model can qualitatively replicate these findings. The linchpin between the uncovered varying sensitivity of household debt to shocks in short-rates within this model is the share of adjustable-rate mortgages on overall mortgages. Picking up the variation over time, we address the resulting costs of reducing mortgage debt via hikes in policy rates in terms of unemployment. The resulting sacrifice ratios reveal that leaning against high mortgage debt by adjusting policy rates becomes more and more costly over time. With counterfactuals, we show two things. First, this result cannot be addressed to the respective Fed chairmanship, as there is no substantial shift in the policy rule over time. Second, the accumulation of household debt cannot be assigned to monetary policy shocks, as they only play a minor role for the path of mortgage debt.

The second paper focuses on the effects of monetary policy on the risk-taking of European banks. Starting with a brief illustration of the banking landscape in Europe with a focus on banks' margins and different private non-financial sector credit standards, we introduce a measure that relates adjustments in credit standards to the prevailing economic conditions. The intention behind this is to evaluate if European banks appropriately adjust their lending standards, or if they show e.g. an over-proportionally strong reaction within their lending standards when they face, for instance, expansionary monetary policy. Thus, we incorporate our measure into vector-autoregressive models and indeed find that expansionary monetary policy induces over-proportionally strong adjustments in private non-financial sector credit standards. Our finding is slightly more pronounced if we focus on a sample that starts in the Financial Crisis. The quantitative reaction of credit growth to expansionary monetary policy indicates only slight increases that are primarily driven by lending for house purchases. This alternative approach to empirically assess the risk-taking channel within the transmission of monetary policy opens a new qualitative perspective for the hardly assessable risk-taking channel.

The third paper tackles the sensitivity of various asset classes to monetary policy, conditional on different risk regimes. After a short outline about asset prices' determinants, we start with the extraction of risk-related factors from sets of candidate variables. The respective sets consist of either macroeconomic, financial, or political risk variables. These factors augment a threshold-vector-autoregressive model that let us explicitly distinguish between high or low states of the aforementioned types of risk. We illustrate that especially during severe crises periods the delimitation among these types of risk becomes a challenging task. With our model, we unveil pronounced state-dependency in the asset prices' reactions to unexpected changes in short-rates. The degree of state-dependency, i.e. the susceptibility of asset prices to monetary policy shocks, conditional on a high- or low risk-regime of a specific type, varies. Equity of industrial firms and non-investment-grade corporate bond yields show very pronounced state-dependency if we distinguish between high or low states of macroeconomic risk. The sensitivity of investment-grade corporate bond yields is most divergent if we differentiate between high and low political risk. Financial equity shows most pronounced differences across states of high or low financial risk, with a surprisingly positive reaction to hikes in short-rates.

Tackling the nexus between income inequality and monetary policy falls to the fourth and last paper of this doctoral thesis. In a first step, we focus on the effects of monetary policy on income dispersion, we use Gini coefficients of market (i.e. gross) and disposable (i.e. net) income. We do so for several countries that differ by their respective degrees of redistribution. While all of them experience increases in the Gini coefficients of gross income when facing expansionary monetary policy shocks, countries that redistribute more have no increases in net income inequality. Using data from national accounts, we find that the disproportional surge in capital income relative to labor income is the primary driver behind increases in net income inequality. Thus, the net effects of monetary policy on disposable income depend on the design of national tax systems and the degree of governmental intervention and redistribution.

I want to close the preface of this dissertation with some acknowledgments. First of all, I want to thank my primary supervisor Prof. Dr. Peter Tillman. His constant, diligent and very courageous support throughout my entire academic path at the Justus-Liebig-University, especially during the recent years, in which I prepared this thesis, cannot be overemphasized. His engagement and enthusiasm, irrespective of the topic or his busy schedule, maintained continuous guidance that I highly appreciated. Thank you, Peter. Second, my sincere gratitude goes to Prof. Dr. Christina Bannier, my secondary supervisor. Her profound knowledge in finance and banking in combination with exchanging ideas during doctoral colloquiums of the Gießener Graduierendenzentrum (GGS) were very valuable to me. Of course, I am also grateful to my colleagues Annette Meinusch, Paul Rudel, Immaculate Machasio, Lucas Hafemann, David Finck, Daniel Grabowski, and Cornelia Strack. Besides their strong professional capabilities, they shaped a very pleasant and fruitful working environment. I would also like to thank our student assistances Florian Viereck, Sinem Kandemir, Omar Omari, Salah Hassanin, Niklas Benner, Moritz Grebe, and Anisa Tiza-Mimun for their support.

I dedicate this doctoral thesis to my beloved family. My parents Gerd and Petra Schmidt as well as my brother Vincent Schmidt backed me whenever they could. Thank you.

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Mortgage Debt and Time-Varying Monetary Policy Transmission

David Finck[*,1] Jörg Schmidt[*,2] Peter Tillmann[*,3]

We study the role of monetary policy for the dynamics of U.S. mortgage debt, which accounts for the largest part of household debt, between 1957Q1 and 2014Q3. A time-varying parameter VAR model allows us to study the variation in the mortgage debt sensitivity to monetary policy. We find that identically-sized policy shocks have lesser effects the more we move to the present. We use a DSGE model to show that a fall in the share of adjustable-rate mortgages (ARMs) could replicate this finding. Calibrating the model to the drop in the ARM share since the 1980s yields a drop in the sensitivity of housing debt to monetary policy that is quantitatively similar to the VAR results. A sacrifice ratio for mortgage debt reveals that a policy tightening directed towards reducing household debt became more expensive in terms of a loss in employment. Counterfactuals show that this result cannot be attributed to changes in monetary policy itself. The results are consistent with the 'mortgage rate conundrum' found by Justiniano et al.[16] and have strong implications for policy.

Keywords: mortgage debt, monetary policy, debt reduction, time-varying VAR, DSGE

JEL classification: E3, E5, G2

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1.1 Introduction

The build-up of household debt in the U.S. and other countries is often interpreted as a potential risk to financial stability (see Jordà et al., [15]) and a determinant of the overall credit cycle (see Mian et al. [17]). Since the recent financial crisis originated in the U.S. housing market, the mortgage market receives a lot of attention. Mortgage debt is by far the largest component of household debt, as it reflects the single, most important financial decision of most households. Hence, monetary policy affects not only the value of houses but also the dynamics of mortgage debt. A monetary tightening can be expected to curb the build-up of mortgage debt. This is an important channel for monetary policy transmission to households.[1]

In this paper, we study the response of U.S. mortgage debt to monetary policy, starting in 1957Q1 and ending in 2014Q3. We believe a model that allows for time-variation in the link between the Fed and the mortgage market is needed. For this purpose, we use a time-varying parameter vector autoregressive (TVP-VAR) model very close to Primiceri [22]. It allows us to model drifting coefficients and a time-varying variance-covariance matrix.

The choice of this model is based on three observations. First, there is strong evidence that the U.S. economy underwent both structural and institutional changes, with the Great Moderation being the most prominent one. Second, the proceeding global integration with the accompanying structural changes in the world economy contradicts a static framework even for a large economy like the U.S., as emphasized by Canova and Gambetti [7], Boivin [5] and Mishkin [18]. Third, financial liberalization, deregulation and financial innovations like securitizations changed the process of financial intermediation in the U.S. economy. To account for these observations, we use a time-varying framework in which we include four variables: civilian unemployment, GDP-deflator inflation and the trend-deviation of real debt, intended to represent the non-policy block, and a short-rate representing the monetary policy instrument. We differentiate between overall household debt, mortgage debt, and non-mortgage household debt. We assume that the Fed only responds to inflation and employment and restrict all time-varying VAR coefficients in the policy rule other than those related to inflation and employment to zero.[2] Our estimation procedure relies on Markov-Chain Monte Carlo (MCMC) methods as in Nakajima [20].

Our key result is that the reaction of mortgage debt to an identically-sized monetary

[1] See Jordà et al. [14] for historical evidence of the link between loose monetary policy and real estate ending booms.

[2] This restriction is relaxed in the robustness section.

policy shock became much smaller over time. Hence, a monetary policy tightening today reduces household debt much less than the same shock in the 1970s. A 25bp tightening in the 1970s led to a drop in the cyclical component of mortgage debt by about 0.1 percentage points, while the same shock today would result in a drop of only 0.04 percentage points. Importantly, non-mortgage debt of households does not exhibit a decline in its sensitivity to monetary policy.

We also construct a sacrifice ratio that compares the loss in employment to the size of the debt reduction after a policy tightening. Low negative values correspond to high debt reduction costs while high negative values express low ones. We find that the declining sensitivity in mortgages is more pronounced than for unemployment. Hence, towards the end of the sample, it is particularly costly in terms of employment to use a monetary tightening to initiate a reduction in household debt. Our main result is robust to the choice and the ordering of the variables. Counterfactuals in the spirit of Sims and Zha [24] show that the change in the responsiveness of mortgages does not stem from changes in monetary policy itself. The finding fits to the 'mortgage rate conundrum' put forward by Justiniano et al. [16]. They argue that the link between Treasury yields, which party reflects monetary policy, and rates on mortgages weakened over time. Hence, both papers stress the role of some underlying structural changes in the mortgage market that impair the monetary policy transmission mechanism.

To explain our findings, we study the interaction of the interest rate elasticity of mortgages with the share of adjustable-rate mortgages (ARM). The literature points to the ARM share as a key determinant of policy transmission to the housing market (see, among others, Calza et al. [6]). The ARM share in the U.S. exhibits a decline since the early 1980s, where the ARM data starts. This encourages us to take a DSGE model of Alpanda and Zubairy [2] and examine variations in the ARM share. The model features a housing market and an occasionally binding credit constraint along the lines of Iacoviello [12]. The impact of the ARM share is nonlinear: a drop in the ARM share causes a less than proportional decline in the interest rate elasticity of mortgage debt. We calibrate the model to the ARM share in 1982, leaving all other parameters at their sample average, and to the ARM share at the end of the data sample. The resulting responses of mortgage debt to a simulated 25bp tightening shock quantitatively match the estimated decline in the response of mortgages to policy shocks.

Our results have important policy implications. First, a weaker transmission of policy impulses to the mortgage market, but not to the real economy, implies that monetary policy is not the right instrument to reduce household debt. A policy tightening at the end of our sample, intended to curb the build-up of mortgage debt, is both ineffective and expensive in terms of foregone employment. Hence, we would advise against using monetary policy to counteract financial risks related to household borrowing.[3]

Second, the results can be interpreted as a case against the 'too low for too long' argument. If monetary policy is relatively ineffective anyway, even before the Financial Crisis, keeping interest rates low for an extended period does not contribute to inflating a credit boom. Our counterfactuals show that for the past 20 years not only the surprise change to the monetary policy stance but also the systematic component of monetary policy contributes little to mortgage debt.

These findings relate to several branches of the literature. In the following, we highlight only those papers that we consider most relevant for us. The first field studies structural features of the U.S. mortgage market and relates them to the strength of the transmission process. Calza et al. [6] present VAR results consistent with the notion that the monetary transmission to housing investment is stronger for a high share of ARMs. We extend this line of research by looking at the U.S. economy over time, not at the cross-section of countries that differ in the average ARM share. Ben Zeev [4] presents a partial equilibrium model of the housing market, in which a high share of ARM mortgage contracts amplifies the effect of an interest rate shock. He also presents empirical evidence consistent with this finding. The ARM share is used to let the economy interact with a credit supply shock. Carriga et al. [8] build a general equilibrium model with incomplete asset markets in which monetary policy affects housing investment by changing the cost of new mortgages. A high ARM share again intensifies the response of the economy to the monetary policy impulse.[4] In addition, the result of this paper can be interpreted as an equivalent to Justiniano et al.'s [16] 'mortgage rate conundrum'. They establish the finding that the connection between mortgage interest rates and Treasury rates broke down in 2003. Hence, the policy tightening of the Fed in 2004 did not lead to higher mortgage rates. Paul [21] also uses a TVP-VAR model to study the policy transmission to various asset prices. He finds that the transmission to house prices was particularly weak before the 2008-9 financial crisis.

The remainder of this paper is structured as follows: section two sketches the evolution of mortgage debt. Section three introduces the TVP-VAR model and details

[3] Alpanda and Zubairy [2] find that e.g. Loan-to-Value ratios are better macroprudencial policy tools to counteract high indebtedness than monetary policy.

[4] Harding and Klein [11] also study the nonlinear impact of monetary policy on the U.S. housing market. They show that monetary policy is effective in periods of deleveraging but not during the build-up of household leverage.

about the estimation technique. Section four discusses the main results. Section five focuses on the role of adjustable-rate mortgages for our results and presents results from a DSGE model. Sections six and seven present counterfactual analyses and robustness checks, respectively, and section eight concludes.

1.2 Mortgage debt

The paper focuses on mortgages held by U.S. private households, which are the main component of overall household debt. Panel (a) in Fig. (1.1) depicts the development of post-war real household debt.[5] There has been a steady increase in household debt and mortgage debt, respectively, until the eve of the Great Recession.

For this paper, we look at the cyclical component of real mortgage debt, which we derive from Baxter and King [3] filtering the original series. The filter has a band-length of eight and lets frequencies between four and 64 quarters pass. With this calibration, we account for the average length of financial and debt cycles in the U.S. and take into account that these cycles are about twice as long as the business cycle, as outlined by Alpanda and Zubairy [2]. The resulting cyclical series, the mortgage gap, is depicted in panel (b) of Fig. (1.1).

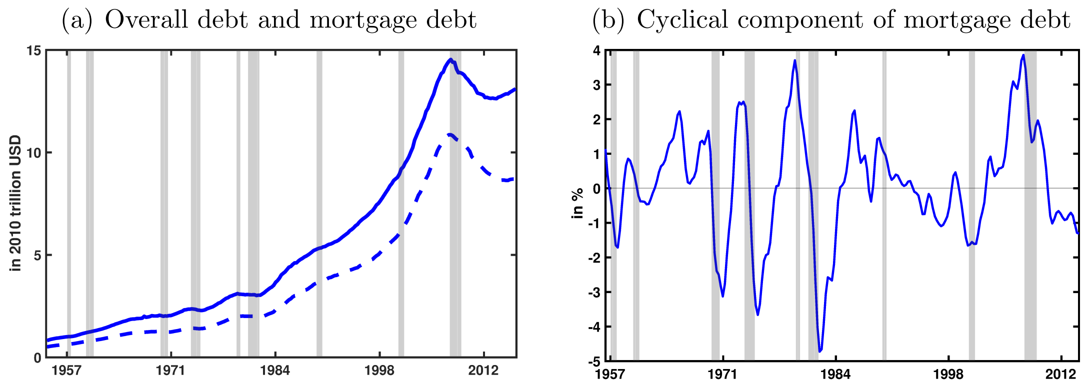

Figure 1.1: Household debt in the U.S.

Notes: The solid line in panel (a) is overall real household debt. The dotted line in panel (a) shows real mortgage debt. Panel (b) shows the cyclical component of Baxter-King-filtered mortgage debt (blue-solid). The shaded areas reflect NBER-dated recessions.

We find that the mortgage gap fluctuates between 4% and -5% and peaks before each recession. During a recession, most gaps turn negative. This variable is the key input into our empirical model. For robustness, we also use the cyclical component

[5] Obtained from FRED, identifiers:
Household Debt: CMDEBT
Mortgage Debt: HHMSDODNS.

derived from a Hodrick-Prescott-Filter with a very high λ[6]. This alternative filtering approach does not affect the results outlined in the following in a notable manner.

1.3 The empirical model

The main tool for our empirical analysis is a series of VAR models, whose structure is time-varying. We start with the time-invariant VAR model in order to introduce a few key elements and to fix notation.

1.3.1 Structural VAR model

A standard time-invariant structural VAR is defined as

$$Ay_t = D + F_1 y_{t-1} + ... + F_s y_{t-s} + \epsilon_t, \qquad t = s+1, ..., T \qquad \epsilon_t \sim \mathcal{N}(0, \Sigma\Sigma') \tag{1.1}$$

where y_t is a $k \times 1$ vector of observed variables, ϵ_t a $k \times 1$ vector of structural shocks, D is a $k \times 1$ deterministic component, e.g. a constant, and $A, F_1, ..., F_s$ are $k \times k$ matrices of coefficients.

The vector y_t contains four variables[7], in quarterly frequency, starting in 1957Q1 and ending in 2014Q3. The first is the unemployment rate u_t, which is our measure of economic activity. The second is inflation, π_t, measured as the year-on-year growth rate of the GDP deflator. The third variable is the cyclical component of real mortgage debt derived before. Our fourth variable is supposed to reflect the Fed's policy instrument. We use the effective federal funds rate, i_t, augmented with a shadow rate during periods characterized by the zero-lower-bound (ZLB).[8] Hence, the vector of endogenous variables is given by $y_t = [u_t, \pi_t, d_t, i_t]'$. We refer to the first three variables as the non-policy block of the VAR system, for reasons to become clear below.

The simultaneous relations of structural shocks are specified by recursive identifica-

[6]Referring to Alpanda and Zubairy [1], we set $\lambda = 10,000$ to account for the very low frequency of debt cycles.

[7]Obtained from FRED, identifiers:
Unemployment Rate, U-3 measure of labor under-utilization: UNRATE.
GDP-Deflator: GDPDEF.
Effective Federal Funds Rate and Shadow Rate: FEDFUNDS and Wu & Xia [25].

[8]We also conduct robustness checks by dropping out the period characterized by the ZLB. The results remain similar and are available upon request.

tion, assuming that A is lower-triangular as[9]

$$A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{kk-1} & 1 \end{bmatrix}. \tag{1.2}$$

Premultiplying both sides by A^{-1}, the model can hence be rewritten as

$$y_t = c + B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1}\Sigma\varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, I_k), \tag{1.3}$$

where $c = A^{-1}D$ and $B_j = A^{-1}F_j$ for $j = 1, ..., s$. The main diagonal elements of Σ, specified as,

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{bmatrix}. \tag{1.4}$$

reflect the standard deviation of our structural shocks ε_t. Stacking all elements of c and B_i, we get the $k + (k^2 s) \times 1$ vector B. Defining $X_t = I_k \otimes [1, y'_{t-1}, ..., y'_{t-s}]$, the model can be rewritten in reduced-form as

$$y_t = X_t B + A^{-1}\Sigma\varepsilon_t. \tag{1.5}$$

The ordering of variables in y_t implies that the monetary policy shock, which we are primarily interested in, does not contemporaneously affect the non-policy block. This assumption is standard in the literature, see Christiano et al. [9]. As a matter of fact, our VAR model includes cyclical mortgages, which are not a standard variable in VAR models. However, we believe the recursive identification remains plausible even if debt is included. Keep in mind that it is unlikely that mortgages, which appear to be an inert variable, contemporaneously respond to monetary policy.

Including mortgages also implies that, in principle, the monetary policy reaction function incorporated in the VAR model allows for feedback from mortgages to monetary policy. Hence, the Fed could respond to real mortgages. Since we want to

[9]Note that the lower-triangular specification of A (and thus A^{-1}) in Eq. (1.2) is widely used and enables us to easily identify structural shocks (as for example monetary policy shocks) by recursive ordering, although the examination of implications for the economic structure may require more complicated identification schemes.

keep the model as close as possible to a standard VAR model, even when including mortgages, we restrict the response of monetary policy to mortgages to zero across all lags.[10] A detailed description of this approach can be found in the appendix, section (1.9).

Finally, it remains to specify the lag order of the VAR system. Our choice of two lags is the result of two considerations. The first is that we want our model to be as parsimonious as possible. This is important, as the time-varying model introduced below is heavily parameterized. Second, if we believe the data generating process is affected by structural breaks, which is why we estimate a time-varying model after all, standard lag selection criteria are no longer valid and offer no guidance to select an appropriate lag-length.[11]

Below, we will explain the VAR model we use to understand policy effects on the U.S. mortgage market, for which the conjecture of constant parameters, and, hence, a time-invariant transmission process might be an inappropriate assumption. For this reason, we allow for time-variation in our modeling framework.

1.3.2 The TVP-VAR model

Our time-varying parameter VAR is specified as

$$y_t = X_t B_t + A_t^{-1} \Sigma_t \varepsilon_t, \tag{1.6}$$

where all parameters, i.e. the VAR coefficients captured in B_t, the simultaneous relationships among the endogenous variables captured in A_t as well as the stochastic volatility of our structural shocks captured in Σ_t, are time-varying. Let $a_t = [a_{21,t}, \cdots, a_{kk-1,t}]'$ be the vector of non-zero and non-one elements of A_t (i.e. the lower-triangular elements of A_t and $h_t = [h_{1,t}, \cdots, h_{k,t}]'$ with $h_{it} = \log \sigma_{it}^2$ for $i = 1, \cdots, k$. Following Primiceri [22], we assume the following dynamics of the model's parameters

$$B_{t+1} = B_t + \eta_{Bt} \tag{1.7}$$

$$a_{t+1} = a_t + \eta_{at} \tag{1.8}$$

$$h_{t+1} = h_t + \eta_{ht}, \tag{1.9}$$

[10] For robustness, we also estimate a TVP-VAR in which this restriction is not imposed, see section (1.7). The results do not vary notably.

[11] However, the lag-length selection did not affect our main results qualitatively.

which are jointly normally distributed as

$$V = Var\left(\begin{bmatrix}\varepsilon_t\\ \eta_{Bt}\\ \eta_{at}\\ \eta_{ht}\end{bmatrix}\right) = \begin{bmatrix} I_k & 0 & 0 & 0\\ 0 & \Sigma_B & 0 & 0\\ 0 & 0 & \Sigma_a & 0\\ 0 & 0 & 0 & \Sigma_h\end{bmatrix}, \qquad (1.10)$$

where $B_{s+1} \sim \mathcal{N}(\mu_{B0}, \Sigma_{B0}), a_{s+1} \sim \mathcal{N}(\mu_{a0}, \Sigma_{a0})$ and $h_{s+1} \sim \mathcal{N}(\mu_{h0}, \Sigma_{h0})$.
Note that all parameters follow a random walk process. Although the random walk process is non-stationary, its assumption can capture both gradual and sudden structural changes (see, for instance, Nakajima [20] and Primiceri [22]). However, the random walk assumption also bears the risk that, besides the true movements, the time-varying coefficients also capture spurious movements, as the parameters are allowed to freely move under this assumption of non-stationary.

1.3.3 Estimation

In order to estimate our TVP-VAR model, we rely on MCMC methods. Our estimation procedure mainly follows Nakajima [20] and can be summarized as follows: given the data $y = \{y_t\}_{t=1}^T$, $\omega = (\Sigma_B, \Sigma_a, \Sigma_h)$ and our prior density $\pi(\omega)$, we use the following MCMC algorithm to draw samples from posterior $\pi(B, a, h, \omega|y)$:[12]

1. Initialize B, a, h and ω.
2. Sample $B|a, h, \Sigma_B, y$.
3. Sample $\Sigma_B|B$.
4. Sample $a|B, h, \Sigma_a, y$.
5. Sample $\Sigma_a|a$.
6. Sample $h|B, a, \Sigma_h, y$.
7. Sample $\Sigma_h|h$.
8. Go back to 2.

1.3.4 Priors

Priors need to be specified for the starting values of our MCMC algorithm (i.e. for the initial state of the time-varying parameters) and for the i^{th} diagonal element of the covariance matrices. There are mainly two common practices for specifying the initial state. The first approach follows Primiceri [22] and chooses a prior that is normally-distributed and whose mean and variance are based on a time-invariant

[12]Accordingly, $B = \{B_{s+1}, ..., B_T\}$, $a = \{a_{s+1}, ..., a_T\}$ and $h = \{h_{s+1}, ..., h_T\}$.

VAR model estimated from, say, the first ten years. The potential drawback of this approach is that we lose these observations for the estimation of our model, as in an ideal Bayesian setting, the prior must not contain any information based on the sample. Second, from the standpoint that we do not have any information about the initial state a priori, setting diffuse priors for the initial states is another option. In particular, the initial state of our parameters has flat priors, set as

$$B_{s+1} \sim N(0, 10 \cdot I), \qquad a_{s+1} \sim N(0, 50 \cdot I), \qquad h_{s+1} \sim N(0, 50 \cdot I). \tag{1.11}$$

Of course, the prior choice for the hyper-parameters can affect posterior inference, although Σ_B, Σ_a and Σ_h do not parameterize time-variation in the first line but only prior beliefs about the degree of time-variation. However, the priors should be carefully chosen because our model has many parameters to estimate. This holds even more for the coefficients as well as for stochastic volatility, as their processes are modeled as a non-stationary random walk process. Thus, tight priors for the covariance matrix of the random walk processes might avoid ill-determined behavior of the parameters. It should be noted that in general the time-varying VAR coefficients require a tighter prior than the time-varying variance-covariance matrix. Therefore, we choose a rather tight prior for Σ_B and rather diffuse priors for Σ_a and Σ_h. More precisely, we set the following priors for $\Sigma_B, \Sigma_a, \Sigma_h$, assuming they follow a multivariate gamma distribution:

$$(\Sigma_B^2)_i \sim G(25, 6 \cdot 10^{-5}), \qquad (\Sigma_a^2)_i \sim G(4, 0.05), \qquad (\Sigma_h^2)_i \sim G(4, 0.05).$$

To compute the posterior estimates, we draw $N = 50,000$ draws and discard the first $45,000$ draws, as samples that have been generated in early iteration steps are likely to be not representative for the true posterior distribution.

1.4 Results

The advantage of our TVP-VAR model is that we can show time-varying effects of monetary policy shocks. This time-variation is not only driven by the estimated VAR parameters, B_t, but also by the shock-impact matrix, A_t^{-1}, as well as the stochastic volatility of the covariance matrix, Σ_t. To study the results, we first discuss the time-varying impulse response functions generated by our model. We then look at time-variation in the relative responses of mortgage debt and unemployment in order to characterize the trade-off that results from a policy-rate-induced reduction of debt.

1.4.1 Responses to a monetary policy shock

In this section, we discuss the time-varying effects of monetary policy shocks on the endogenous variables. Fig. (1.2) shows the mean impact of a 25bp monetary policy shock on unemployment and inflation. We are able to show responses for a shock originating at each point in the effective sample period. Panel (a) shows the response of unemployment. We find that unemployment increases after a policy tightening. The main finding is that the sensitivity of unemployment to a monetary policy shock declines over time and reaches a low in the early 2000s. After that, unemployment becomes slightly more responsive to monetary policy. We can also see a slight shift in the timing of the peak response indicating a more inert transmission of monetary policy shocks on unemployment.

Panel (b) reports the response of inflation. For shocks originating in the first decade of the sample, we observe a strong price puzzle, i.e. an increase in inflation. Since the 1970s and early 1980s, the time when Paul Volcker became Fed Chairman, the price puzzle is small and negligible. Most importantly, we also find a decline over time in the response of inflation to monetary policy. This decline, however, is weaker than for unemployment.

The main finding of this paper is shown in Fig. (1.3), which displays the time-varying reaction of mortgage debt to a monetary policy tightening. The response becomes much smaller over time. Similar to unemployment and prices, mortgage debt exhibits the strongest response at the beginning of our sample. Since then, the impact gradually declines, reaching its lowest sensitivity at the end of our sample, with a short interruption during the Volcker-period and during the end of the nineties. For most recent dates, the peak response of mortgage debt to monetary policy is a third or a quarter of the response that we see at the beginning of our sample.

To get a full view on the changing nature of monetary policy transmission that accounts for estimation uncertainty, we show selected cross-sections of our model-implied impulse response functions with their respective 16^{th} and 84^{th} percentiles of the posterior distribution of the estimated time-varying VAR-parameters. Fig. (1.4) to Fig. (1.7) show the time-varying reaction of our endogenous model variables one, four, eight, and 16 quarters after the shock. Thus, we slice through Fig. (1.2) and (1.3) at a specific horizon of the impulse response. We also add the response of the short-rate itself. The percentiles, 16^{th} and 84^{th}, of the underlying estimated posterior distribution allow us to judge the magnitude and statistical significance of the responses.

We can observe that the initial significance of our observed price puzzle begins

to vanish over time. Unemployment becomes increasingly insensitive to monetary policy since the early 1990s when we consider the corresponding percentiles. The persistence of interest rate responses to monetary policy shocks does not fluctuate much over time. For mortgage debt, we see the diminishing significance of the reaction over time quite well, especially in Fig. (1.5) and Fig. (1.6).
Finally, we extract the maximum impact of the monetary policy shock on mortgage debt as well as the time at which the maximum response occurs. Both are in Fig. (1.8). This allows us to better describe the shift in the sensitivity of mortgage debt to monetary policy over the sample period. We can see the general tendency of diminishing effects of monetary policy shocks, with responses becoming non-significant at the end of our sample. We also find that the maximum impact of the policy shock occurs later over time.
The decline in the sensitivity of mortgage debt has strong implications for monetary policy, which we will now study in detail. Keeping in mind that the reduced-form model is not suitable for normative policy analysis, our results suggest that using monetary policy to curb household debt is difficult. This is because the effectiveness strongly varies over time. This also implies that the costs of such a reduction in terms of unemployment also vary over time. We will pick up this thought in the following section.

1.4.2 The sacrifice ratio of debt reduction

Let us consider a central bank that aims at using a hike in the policy rate to obtain a debt reduction of households. Since we base this thought experiment on a reduced-form model, we should stress that we do not intend to derive normative implications. Rather, we want to shed light on when a debt reduction as a result of a monetary tightening is relatively expensive or cheap, respectively. For that purpose, we invoke the concept of the sacrifice ratio, which answers the question of how costly a disinflation is in terms of unemployment. We construct a measure that shows how expensive a debt reduction is in terms of unemployment, which fluctuates over the sample period. This measure, Γ_t, is the ratio of the response of mortgage debt, d, and the response of unemployment, u, for horizon h. For each horizon, the nominator and the denominator are the cumulative mean impulse-responses

$$\Gamma_t = \frac{\sum_{i=1}^{h} IRF_{t+i}^{d}}{\sum_{i=1}^{h} IRF_{t+i}^{u}}, \tag{1.12}$$

where the horizon h can be interpreted as the relevant horizon for policy makers. Consider a policy shock that leads to a reduction in debt and to an increase in unemployment. Hence, the ratio is negative. If for the same loss in employment debt faces less reduction, this reduction becomes relatively costly. On the opposite, if we can achieve a relatively high reduction of debt per unit increased unemployment with the respective policy shocks, we get a relatively cheap debt reduction. An increase in Γ_t would thus be consistent with a more costly reduction, i.e. for a one unit increase in unemployment we only get a relatively small reduction in debt. We consider two alternative horizons: $h = 8$ and $h = 12$ quarters. Fig. (1.9) displays the ratio for the two horizons h. We can see an upward trend in both series. Hence, a debt reduction becomes more expensive over time. The trend is broken only during the late 1990s.

The path of Γ is quite intuitive and mirror-images the time-varying sensitivity of unemployment and debt in Fig. (1.2) and Fig. (1.3): debt reductions induced by monetary policy are (relatively) cheap if either the sensitivity of unemployment to monetary policy shocks is low or the sensitivity of mortgage debt is high.

1.5 The role of adjustable-rate mortgages

Many structural forces could potentially be responsible for the decline in the sensitivity of mortgages to monetary policy. Calza et al. [6] highlight key parameters that affect how sensitive mortgages are to the monetary policy stance. Among them, the ARM share plays an important role. In the U.S. economy, this share declined over time. Fig. (1.10) plots the ARM share since the early 1980s. While in 1983 the share is about 60%, it fell to only 10% in 2011.[13]

The share of ARM has some interesting implications for the transmission of monetary policy, as the sensitivity of mortgage debt to short-term interest rates is a key channel of the transmission of monetary policy to the housing market and the economy in general. More precisely, given a scenario where mortgages are closely linked to short-term interest rates, unexpected hikes in the policy rate quickly shift both cash flows and mortgage payments, in particular for existing borrowers. In this scenario, changes in the policy rate also affect the initial cost of new home loans, which in turn affects the demand for housing.

However, this is not the case for the U.S. As mentioned before, the share of ARMs has declined in the last three decades, implying that homebuyers mostly preferred fixed-rate mortgages (FRM) over ARM. We therefore expect that the transmission of monetary policy shocks to the economy is linked to the ARM share. In particular,

[13] Moench et al. [19] discuss the reduction in the ARM share in the U.S. and explain it in terms of financial innovations such as an increase in securitization and a shifting term structure of interest rates.

we expect that the transmission is more powerful in a scenario where the ARM share is high.
The fall in the ARM share since the early 1980s corresponds to the decline in the sensitivity of mortgages to monetary policy documented before. To illustrate this point, Fig. (1.11) plots the impulse responses following monetary policy shocks originating in 1983Q3 and 2011Q3, respectively. As we can see, the impact of a 25bp monetary policy shock on mortgages in the early 1980s exceeds by far the non-significant impact of the same shock at the end of our sample. Thus, in the following, we want to shed light on possible drivers of this sharp decrease in mortgage debt sensitivity with respect to monetary policy shocks and highlight the ARM share as a promising candidate to explain the declining sensitivity.

1.5.1 Some simple regressions

To obtain a first impression of the determinants of time-variation in the policy-impact on mortgages, we regress the dynamic impulse response functions on the ARM share. We also control for other characteristics of the prevailing contracts in this market. We do so for the peak responses of mortgage debt,

$$IRF_{t,t+peak} = c + \gamma X_t + \varepsilon_t,$$

as well as for impulse responses cumulated up to horizon h,

$$\sum_{\tau=1}^{h} IRF_{t,t+\tau} = c + \gamma X_t + \varepsilon_t,$$

where t is the timing of the shock and τ is the timing of the response. Possible candidate variables for X_t other than the ARM share are the national average of the loan-to-value ratio (LTV) and the average effective interest rate payed for mortgage contracts (effective rate), both also provided by the Federal Housing Agency's Interest Rate Survey. The vector γ collects the coefficients and ε is a white-noise error term. It should be stressed that such a regression is illustrative only. The explanatory variables are by no means exogenous, structural determinants. Nevertheless, we believe such a regression to be informative. Below, we simulate a structural model to corroborate our findings.
Fig. (1.12) shows the respective correlation of these variables with the regressors mentioned above. At first glance, we can see that the ARM share seems to be negatively correlated with all types of regressors. Thus, for high ARM shares we should find lower impulse responses. The same holds for the LTV ratio and the

effective rate on mortgage debt.
To account for possible non-linearities between the impulse responses and the ARM share, we also include the squared ARM share into our regression. This is primarily motivated by the implications of our DSGE model described in the following section. The shape of responses to monetary policy shocks for different ARM shares, depicted in Fig. (1.24), indicates a non-linear relationship. Tab. (1.2) shows the outcome of the respective regressions. When the ARM share increases, the mortgage debt falls more strongly after a policy tightening.
This finding holds in most regressions depicted in Tab. (1.2). In almost all regressions, the control variables show the expected sign. When the LTV ratio is high, refinancing the existing burden of debt is relatively costly and thus incentives to reduce debt are high, respectively. Similar considerations hold for the effective rate. If financing debt is expensive, households tend to reduce debt if policy tightens. Summing up, we conclude that the ARM share plays an important role in explaining the time-varying sensitivity of mortgage debt to monetary policy shocks.[14]

1.5.2 A DSGE-Model with mortgage contracts

While the previous regressions are illustrative, eventually a structural model is needed to shed light on the impact of a shift in the ARM share on the strength of policy transmission. Therefore, we resort to the DSGE model by Alpanda and Zubairy [2].
In short, the model builds a closed-economy DSGE with housing and household debt as well as an occasionally binding credit constraint. The model features two types of households: patient households (savers) and impatient households (borrowers). Excessive household debt is caused by exuberance shocks on expectations on house prices, thus driving a wedge between actual and fundamental values.
Importantly, the model allows the average duration of the fixed interest rate for loans to be shorter than the full amortization duration of the underlying loan itself. In simple words, the interest rate on new mortgage loans is decomposed into a fraction carrying a fixed mortgage interest rate and a fraction of existing loans that is refinanced each period.
We use the model to simulate impulse responses to monetary policy shocks for different calibrations of the ARM share. We simulate impulse responses for mortgage debt to a 25bp monetary policy shock, which is consistent with the definition of the policy shock in the TVP-VAR. In the first case, the 'low share' case, we use the

[14] Local projections in the spirit of Jordà [13] indicate similar findings, the results are available upon request.

same overall calibration as Alpanda and Zubairy [2], including the interest rate adjustability of mortgages based on a 10% ARM share, which we can observe at the end of our sample. In the second case, the 'high share' case, we re-calibrate the interest rate adjustability parameter to meet an ARM share of 60%. This reflects the share of ARMs in 1982, the beginning of data availability for this series. We keep everything else similar to the benchmark case.

In Fig. (1.13), we compare the impulse responses to 25bp monetary policy shock for both the DSGE and the TVP-VAR. Two things stand out. First, similar to our time-varying VAR, there is a weaker reaction of mortgage debt to monetary policy shocks when the ARM share is low. Second, the amplitude of both the DSGE and the TVP-VAR are nearly identical in the high share case with a 0.05% drop in mortgages. For the low share case, the TVP-VAR shows a slightly weaker response. However, this can likely be attributed to the fact that our recalibration was solely based on the different fraction of ARM shares, although the interest rate duration is of course based on different factors, including home equity loans and repayments, among others.

Additionally, we can see that the relationship between the ARM share and the size of the mortgage reaction to a restrictive 25bp monetary policy shock shows a non-linear pattern. Fig. (1.24) plots a set of peak responses with their corresponding ARM shares. As we can see, this convex, model-implied nexus underpins the appropriateness of our TVP-VAR model as well as the inclusion of the squared ARM share in section (1.5.1). Summing up, the DSGE model provides further evidence for the important role of ARM shares in the transmission of monetary policy shocks. The empirically observed drop in the ARM share since the early 1980s leads to impulse responses that are quantitatively very similar to the responses derived from the TVP-VAR.

1.6 Counterfactual analysis

Thus far, our results provide evidence that the transmission of monetary policy shocks may have become weaker over time, based on the drop in the amplitude of impulse responses for the non-policy block, i.e. u, π, d. Moreover, from the standpoint that our model is supposed to uncover the time-varying structure of the economy, relative cumulative responses provide evidence that periods exist in which reducing debt might be less costly than in others. However, this section seeks to isolate the Fed's role from the rest of the economy. Thus, we report results for some counterfactual experiments that might be of interest. Counterfactual analyses have been widely used (see, for instance, Primiceri [22] and Sims and Zha [24]). They are an informative possibility to establish the role of the Fed in the weaker transmission of monetary policy shocks observed in section (1.4) on the one hand, but also on high volatility episodes of debt on the other. Although there are plenty of interesting experiments in general, we discuss two main results we believe are the most relevant in general and for our purpose in particular.

In a first experiment, we document the path of mortgage debt in a scenario with suppressed monetary policy shocks in an otherwise time-varying fashion, answering the question of what we would have observed if no monetary policy shocks would have hit the economy. This uncovers the time-varying contribution of monetary policy shocks to the fluctuation of household debt that has been observed in reality. In a second experiment, we seek to underpin our finding of a weaker transmission. In particular, the question remains whether the weaker impulse responses stem from possible shifts in the policy rule. This is particularly important in episodes where the structure of the economy implies relatively cheap debt reductions on the one hand, but more (costly) fluctuation on the other. If an underlying monetary policy regime leads to systematically higher (lower) fluctuation in debt, intentional debt reductions require a more (less) aggressive behavior of the central bank to achieve the same outcome. By doing so, we isolate the effect of possible regime switches. We fix both the average VAR-parameters as well as the simultaneous relationship among variables over the corresponding period. This is done for the three most recent chairmanships, including the Volcker regime (1979-1987), the Greenspan regime (1987-2006) and the Bernanke regime (2006-2014).

The procedure follows Primiceri [22] and Sims and Zha [24] and can be summarized as follows: since we have drawn all parameters from the joint posterior distribution, we can reconstruct the independent identically-distributed sequence of unit-variance structural shocks. Starting from an arbitrary point, it is possible to simulate counterfactual data series, obtained by using the parameters of our TVP-VAR, but with suppressed monetary policy shocks in the first experiment or with time-invariant policy rules in the second.

Experiment one: suppressed monetary policy shocks

Fig. (1.14) shows the simulated path for mortgage debt in the absence of monetary policy shocks, keeping anything else similar to the benchmark case (i.e. drawing from the time-varying parameters). Two things stand out. First, there are episodes where the simulated path and the data are remarkably different. The red ellipses mark episodes where the simulated paths lie outside the 16^{th} and 84^{th} percentiles.

As can be seen, the frequency of such episodes declined during the Great Moderation. Second, the simulated paths are mostly lower (higher) in periods when debt was high (low). Albeit there are episodes of remarkable differences, especially during times of financial turmoil, the simulated path is mostly not too different from the actual path. This shows that there seem to be sources other than monetary policy shocks to explain episodes of high mortgage debt. This finding is underpinned in Fig. (1.15), as the difference between simulated and actual path gradually declined over time.

Experiment two: the role of chairmanships
As mentioned above, the second experiment seeks to uncover possible regime shifts that could account for shifting feedback effects in the economy which in turn might contribute to episodes of high fluctuations.[15]
Fig. (1.16) summarizes the results of our experiment. Focusing on mortgage debt, the upper plot shows the actual data as well as the simulated paths for all different chairs. Clearly, both the simulated paths as well as the actual data cannot be distinguished with the naked eye. Thus, different policy rules cannot account for substantial fluctuations in household debt. The lower plot shows the differences between the actual and simulated paths. Interestingly, the simulated path for a scenario in which the average Bernanke policy rule prevailed throughout the sample is permanently higher than for the other two cases.

1.7 Robustness

The results presented in section (1.4) were derived from a policy rule that contained zero-restrictions. We also assumed a specific ordering of the variables. Additionally, we take a look at other kinds of household debt. Therefore, our robustness section aims to underpin our results for several experiments. As it is common in Bayesian literature, we also evaluate our choice of priors.

Other debt categories
Recall from Fig. (1.1) that the correlation between overall debt and mortgage debt is high. Consequently, one might ask whether the drop in the sensitivity of mortgage

[15] To fully account for the role of regime switches, a more complex model is needed, as in Sims and Zha [24]. However, this problem is mitigated for two reasons. First, we are mainly interested in the consequences of possible shifts in the policy rule, saying that uncovering regime switches itself is not of primary interest for us. The second stems from the fact that our results do not provide evidence in favor of remarkable differences among chairmanships.

debt to monetary policy does also hold for overall household debt and other debt categories. To show that this is not the case, we report the main results for (i) overall household debt and (ii) debt other than mortgages non-mortgage debt, i.e. overall household debt less mortgage debt.[16]

In a first experiment, we estimate a model that includes the cyclical component of overall household debt instead of mortgage debt, keeping anything else identical to the benchmark case. Fig. (1.17) to Fig. (1.18) show the dynamic impulse responses after an identically-sized monetary policy shock after four and eight quarters, respectively. The drop in the sensitivity is less pronounced if we use overall household debt instead of mortgage debt. Fig. (1.19) to Fig. (1.20) show the results of a similar experiment, using the cyclical component of non-mortgages this time. First, it stands out that the response of non-mortgages shows a positive sign over the entire sample. However, the 16^{th} and 84^{th} percentiles always cover the zero line, i.e. it is likely that the impulse responses are not different from zero. Combining the results of these two alternative models, we conclude that (1) the drop in the sensitivity of overall household debt is mainly driven by the mortgage component and (2) we do not observe similar shifts in the sensitivity for other debt categories.

Unrestricted policy rule

Although it is reasonable to assume that the Fed's policy rule does not include a reaction to household debt as depicted in section (3.4), we re-estimate our model without the restriction on the policy rule, keeping all other features of the model untouched. The estimated paths for the lagged coefficients in the policy rule as well as the corresponding parameter in the simultaneous relationship matrix are shown in Fig. (1.22). Interestingly, the lagged coefficients are different from zero. The variation over time is small, which is clearly attributable to the informative prior on Σ_B. This is not the case for the covariance between mortgage debt and the short-rate, as there is much time-variation observable, even though the estimates mostly fluctuate around zero.

The corresponding impulse responses over time are shown in Fig. (1.21). It stands out that the impulse responses are not distinguishable from the baseline case. Similarly to the benchmark case, there is a trend towards a weaker transmission of monetary policy shocks.[17] Summarizing our results, we conclude that including

[16] Non-mortgage debt summarizes all residual debt categories other than mortgages, e.g. consumer credit. We use the same technique to isolate the cyclical component using the Baxter King [3] filter with the same setup as for mortgage debt.

[17] Also the relative cumulative responses of unemployment and mortgage debt show a similar picture. Other results for the unrestricted policy rule are available upon request.

mortgage debt in the policy rule leads to very similar results with the estimated parameters not being different from zero.

Sensitivity to priors

Section (1.4) is based on our particular prior choice. Now, we report the results for alternative prior specifications. First, it stands out that the choice of the priors for the initial states of the Gibbs sampler turns out to be innocuous, the prior choice for Σ_B, Σ_a and Σ_h, however, does not. Of course, the prior choice for these hyper-parameters can affect posterior inference, although Σ_B, Σ_a and Σ_h do not parameterize the time variation directly, only prior beliefs about the time-variation. Choosing looser priors for Σ_B, e.g. $(\Sigma_B^2)_i \sim G(30, 1 \cdot 10^{-3})$ results in much more time-variation, although the estimation procedure becomes inefficient as our convergence tests are unsatisfying. This being said, the model seems to misbehave for looser priors than in our benchmark case, saying that our particular prior choice does not penalize time variation in the coefficients (see Primiceri [22]). Different choices for Σ_a and Σ_h do not affect the results in a significant way. We try both looser and tighter priors, but the results are similar to the baseline model. Summing up, our results are robust against alternative prior choices, as long as the prior for Σ_B is informative enough.

Sensitivity to an alternative ordering

Choosing an alternative cholesky-ordering can, in principle, affect our results, as we alter the linear combinations of the reduced-form error terms which lie behind the structural shocks. For this reason, we check whether alternative orderings, i.e. ordering prices before unemployment, affect our main result. It turns out that the alternative ordering results in very similar results, which implies that our results are also robust to alternating the recursive ordering of the variables.

Alternative variables

Another concern could be related to our choice of variables. For mortgage debt, which we include in deviations from its trend, we also try different de-trending techniques (e.g. the Hodrick-Prescott filter) as well as different settings for the Baxter King [3] frequency filter. The results do not change much. This being said, we also try different combinations of variables, replacing unemployment by GDP-growth (annual, seasonally adjusted) or the output gap as well as GDP-deflator inflation by an inflation rate based on the CPI (annual, seasonally adjusted). It stands out that our qualitative results are robust against different variable selections.

For example, using inflation based on the CPI delivers very much the same qualitative results, albeit there is a severe price puzzle, as can be seen in Fig. (1.23).

1.8 Conclusions

In this paper, we study the role of monetary policy for the dynamics of U.S. mortgage debt, the largest and most important component of overall household debt. In the aftermath of the recent financial crisis, which originated in the U.S. housing market, the mortgage market received much attention.

The main tool of our analysis, a time-varying VAR model with stochastic volatility, allows us to study the sensitivity of mortgage debt to monetary policy over time. We find that since the 1960s the impact of monetary policy on mortgage debt steadily declined. A policy shock in 2014 has a much smaller effect on mortgage debt than a similarly sized shock occurring in 1970. This finding, which is new to the literature, is robust to variations of the model and the parameterization and not driven by changes to monetary policy itself.

We also calibrate a DSGE model for the U.S. economy to replicate our empirical findings. The share of ARMs, a key parameter in the determination of the model-based impulse responses, is shown to have declined strongly since the early 1980s. Once we calibrate the model to alternative realizations of the ARM share, we are able to replicate the decline in the response of debt to monetary policy quantitatively. To the extent the ARM share could be taken as given, this offers a consistent explanation for our findings.

These findings have several implications for monetary policy and the mortgage market. First, our results suggest that, nowadays, monetary policy is a blunt and ineffective tool to engineer a reduction of household debt. The decline in the sensitivity to monetary policy implies that a large policy adjustment is needed to obtain a sizable effect on mortgage debt. This, however, would cause a deep recession. Hence, our results speak against using monetary policy as an instrument to prevent the build-up of household debt.

The second interpretation of our results addresses the role of the Fed in the run-up to the recent financial crisis. It is often claimed that the Fed contributed to inflating house prices by keeping the Federal Funds Target Rate too low for too long. Our results put this claim into perspective. If the sensitivity of mortgage debt to monetary policy in the mid-2000s is low, which is our main result, even persistently low levels of the Federal Funds Rate should contribute little to the rise in mortgage debt before the crisis. Likewise, tightening monetary conditions, as the Fed did after June 2004, should translate into a small decrease in mortgage debt. Of course, we focus on the non-systematic part of monetary policy only within our VAR model. However, even counterfactuals in which we replace the systematic part of monetary policy show that the contribution of monetary policy to the dynamics of mortgage debt has been small.

Our results fit together with the 'mortgage rate conundrum' diagnosed by Justiniano et al. [16]. These authors argue that the empirical link between mortgage rates and longer-term interest rates broke. Hence, there seem to be strong structural changes in the mortgage market and its link to monetary policy. While this paper focuses on mortgage debt, other aspects of this structural shift are left to future research.

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1.9 Appendix

Convergence diagnostics

This appendix assesses the convergence of our MCMC algorithm in the baseline case presented in section (3.4). We applied different experiments to judge how well our chain mixes. Recall that we used 50,000 iterations and discarded the first 45,000. It stands out that choosing different burn-in periods delivered exactly the same results. It is common practice to observe the inefficiency factors for convergence analysis. Simply speaking, the inefficiency factor is the inverse of the relative numerical efficiency measure of Geweke [10] and defined by $1 + 2\sum_{j=1}^{\infty} \rho_j$, where ρ_j is the autocorrelation of j^{th} order for the underlying parameter. Inefficiency factors of around 20 are regarded as satisfactory. Tab. (1.9) reports the inefficiency factors of our entire parameter space. Except for the hyperparameters, the inefficiency factors are on average far below 20. Not taking single outliers too serious as our parameter space is large, we conclude that our chain mixes quite fast.

	Mean	Median	Max	70^{th} Percentile	90^{th} Percentile
V	23.11	17.21	95.7	24.52	43.93
B	2.91	2.63	10.33	3.31	3.95
A	2.89	1.56	16.89	3.33	7.5
Σ	4.26	2.91	25.8	4.96	9.13

Table 1.1: Distribution of inefficiency factors for the entire parameter space.

We also applied the Geweke [10] convergence diagnostic test. The idea can be sketched as follows. For each single parameter, the idea is to compare the first n_0 draws of the chain to the n_1 draws by dropping the corresponding draws in between. The statistics are calculated as $G = (\bar{x}_0 - \bar{x}_1)/\sqrt{\widehat{\sigma}_0^2/n_0 + \widehat{\sigma}_1^2/n_1}$, where $x_j = (1/n_j)\sum_{i=m_j}^{m_j+n_j} x^i$. x^i is the ith draws and $\widehat{\sigma}_j^2/n_j$ is the standard error of $\bar{x}_j$ for $j = 0.1$. We choose n_0 as the first 10% and n_1 as the last 50%. $\widehat{\sigma}_j^2$ is computed using a Parzen window. Of course, G is below 0.05 if the whole chain is stationary, saying that the means of the first n_0 and the last n_1 values are quite similar. However, it turned out that for V 72.09% , for B 61.97%, for A 60.69% and for Σ 56.55% seemed to converge after the first 5,000 draws.

To sum up, the convergence diagnostics seem satisfactory, considering the high parameter space of our model.

Implementation of the short-run restrictions

As explained in section (3.4), we include four variables in our model, that is unemployment u, inflation π, and mortgage debt d as the non-policy block, while a short-term interest rate i is intended to represent the policy block. This implies that our TVP-VAR can be written as

$$\begin{aligned}\begin{bmatrix} u_t \\ \pi_t \\ d_t \\ i_t \end{bmatrix} = \begin{bmatrix} c_t^u \\ c_t^\pi \\ c_t^d \\ c_t^i \end{bmatrix} + \begin{bmatrix} b_{1,t}^{uu} & b_{1,t}^{\pi u} & b_{1,t}^{du} & b_{1,t}^{iu} \\ b_{1,t}^{u\pi} & b_{1,t}^{\pi\pi} & b_{1,t}^{d\pi} & b_{1,t}^{i\pi} \\ b_{1,t}^{ud} & b_{1,t}^{\pi d} & b_{1,t}^{dd} & b_{1,t}^{id} \\ b_{1,t}^{ui} & b_{1,t}^{\pi i} & b_{1,t}^{di} & b_{1,t}^{ii} \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \pi_{t-1} \\ d_{t-1} \\ i_{t-1} \end{bmatrix} + \cdots \\ ...+ \begin{bmatrix} b_{s,t}^{uu} & b_{s,t}^{\pi u} & b_{s,t}^{du} & b_{s,t}^{iu} \\ b_{s,t}^{u\pi} & b_{s,t}^{\pi\pi} & b_{s,t}^{d\pi} & b_{s,t}^{i\pi} \\ b_{s,t}^{ud} & b_{s,t}^{\pi d} & b_{s,t}^{dd} & b_{s,t}^{id} \\ b_{s,t}^{ui} & b_{s,t}^{\pi i} & b_{s,t}^{di} & b_{s,t}^{ii} \end{bmatrix} \begin{bmatrix} u_{t-s} \\ \pi_{t-s} \\ d_{t-s} \\ i_{t-s} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ \tilde{a}_t^{u\pi} & 1 & 0 & 0 \\ \tilde{a}_t^{ud} & \tilde{a}_t^{\pi d} & 1 & 0 \\ \tilde{a}_t^{ui} & \tilde{a}_t^{\pi i} & \tilde{a}_t^{di} & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t^u \\ \epsilon_t^\pi \\ \epsilon_t^d \\ \epsilon_t^i \end{bmatrix}.\end{aligned} \tag{1.13}$$

However, considering the Fed's mandate, it might be reasonable to assume that d should not appear in the interest rate equation (i.e. the policy rule). This implies that $b_{1,t}^{di}, ..., b_{s,t}^{di}$ as well as $\tilde{a}_t^{di}$ should be restricted to zero. The rationale behind this is that the Fed only responds to unemployment u and prices π, but not to debt d. Implementing these restrictions results in a specific interest rate equation within our model:

$$\begin{aligned} i_t =& c_t^i + b_{1,t}^{ui} u_{t-1} + b_{1,t}^{\pi i} \pi_{t-1} + \underbrace{b_{1,t}^{di}}_{\overset{!}{=}0} d_{t-1} + b_{1,t}^{ii} i_{t-1} + ... \\ &... + b_{s,t}^{ui} u_{t-s} + b_{s,t}^{\pi i} \pi_{t-s} + \underbrace{b_{s,t}^{di}}_{\overset{!}{=}0} d_{t-s} + b_{s,t}^{ii} i_{t-s} + ... \\ &... + \tilde{a}_t^{ui} \epsilon_t^u + \tilde{a}_t^{\pi i} \epsilon_t^\pi + \underbrace{\tilde{a}_t^{di}}_{\overset{!}{=}0} \epsilon_t^d + \epsilon_t^i. \end{aligned} \tag{1.14}$$

Summing up, restricting $\tilde{a}_t^{di}$ and $b_{s,t}^{di}$ for all lags to zero results in

$$
\begin{aligned}
\begin{bmatrix} u_t \\ \pi_t \\ d_t \\ i_t \end{bmatrix} &= \begin{bmatrix} c_t^u \\ c_t^\pi \\ c_t^d \\ c_t^i \end{bmatrix} + \begin{bmatrix} b_{1,t}^{uu} & b_{1,t}^{\pi u} & b_{1,t}^{du} & b_{1,t}^{iu} \\ b_{1,t}^{u\pi} & b_{1,t}^{\pi\pi} & b_{1,t}^{d\pi} & b_{1,t}^{i\pi} \\ b_{1,t}^{ud} & b_{1,t}^{\pi d} & b_{1,t}^{dd} & b_{1,t}^{id} \\ b_{1,t}^{ui} & b_{1,t}^{\pi i} & 0 & b_{1,t}^{ii} \end{bmatrix} \begin{bmatrix} u_{t-1} \\ \pi_{t-1} \\ d_{t-1} \\ i_{t-1} \end{bmatrix} + \cdots \\
...+ & \begin{bmatrix} b_{s,t}^{uu} & b_{s,t}^{\pi u} & b_{s,t}^{du} & b_{s,t}^{iu} \\ b_{s,t}^{u\pi} & b_{s,t}^{\pi\pi} & b_{s,t}^{d\pi} & b_{s,t}^{i\pi} \\ b_{s,t}^{ud} & b_{s,t}^{\pi d} & b_{s,t}^{dd} & b_{s,t}^{id} \\ b_{s,t}^{ui} & b_{s,t}^{\pi i} & 0 & b_{s,t}^{ii} \end{bmatrix} \begin{bmatrix} u_{t-s} \\ \pi_{t-s} \\ d_{t-s} \\ i_{t-s} \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ \tilde{a}_t^{u\pi} & 1 & 0 & 0 \\ \tilde{a}_t^{ud} & \tilde{a}_t^{\pi d} & 1 & 0 \\ \tilde{a}_t^{ui} & \tilde{a}_t^{\pi i} & 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t^u \\ \epsilon_t^\pi \\ \epsilon_t^d \\ \epsilon_t^i \end{bmatrix}.
\end{aligned} \tag{1.15}
$$

Figures and Tables

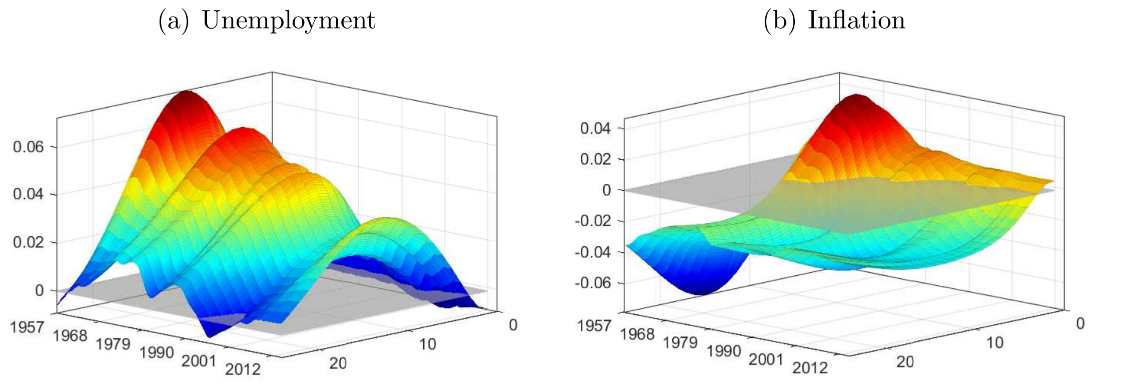


Figure 1.2: Mean responses to a monetary policy shock.
Notes: Results from our baseline TVP-VAR model. The monetary policy shock is 25bp in size.

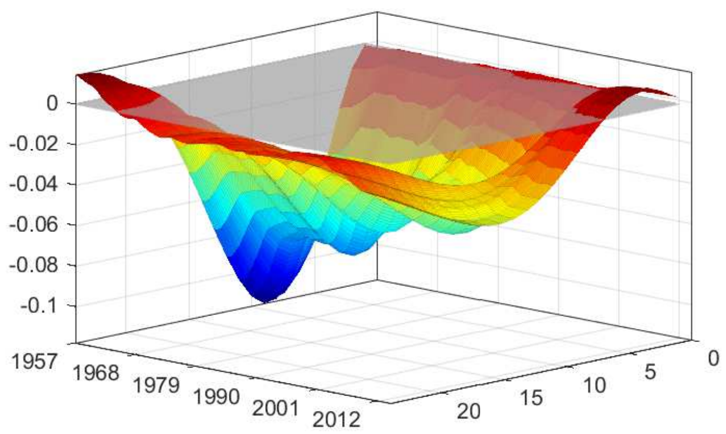


Figure 1.3: Mean responses to a monetary policy shock: mortgage debt.
Notes: Results from our baseline TVP-VAR model. The monetary policy shock is 25bp in size.

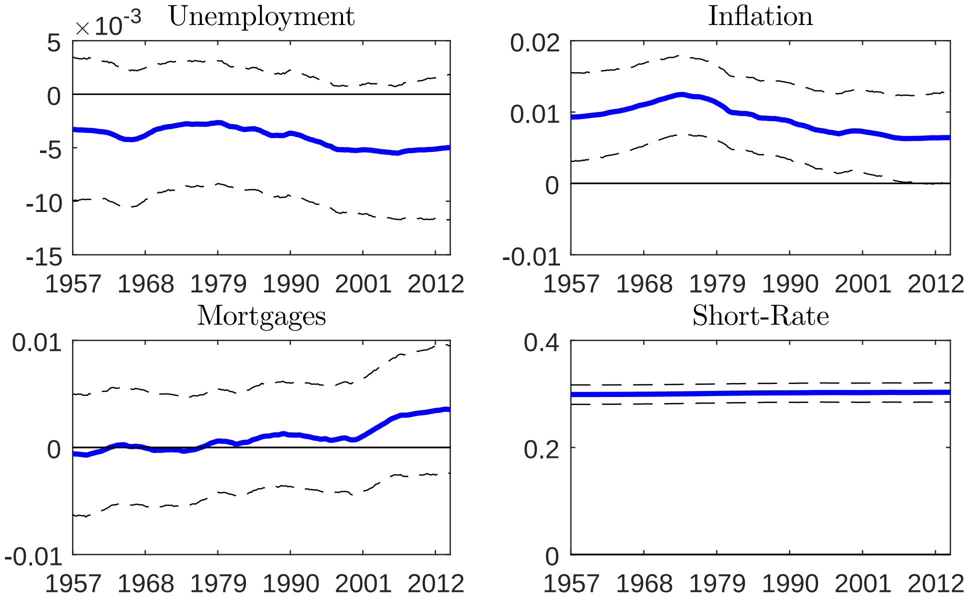


Figure 1.4: Responses to a monetary policy shock after one quarter.

Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (gray-dashed) to an initial monetary policy shock of 25bp after one quarter.

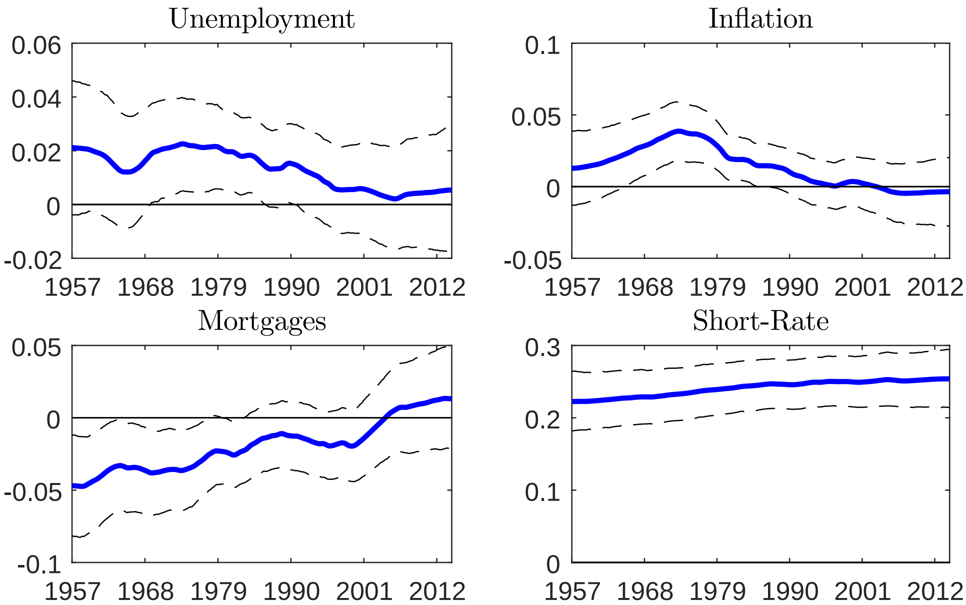


Figure 1.5: Responses to a monetary policy shock after four quarters.

Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (gray-dashed) to an initial monetary policy shock of 25bp after four quarters.

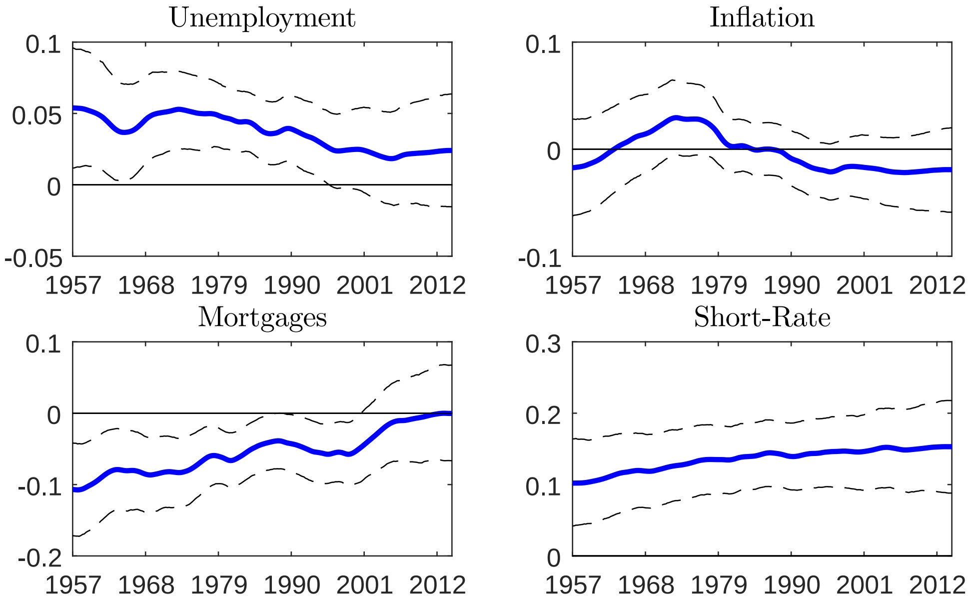


Figure 1.6: Responses to a monetary policy shock after eight quarters.

Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (gray-dashed) to an initial monetary policy shock of 25bp after eight quarters.

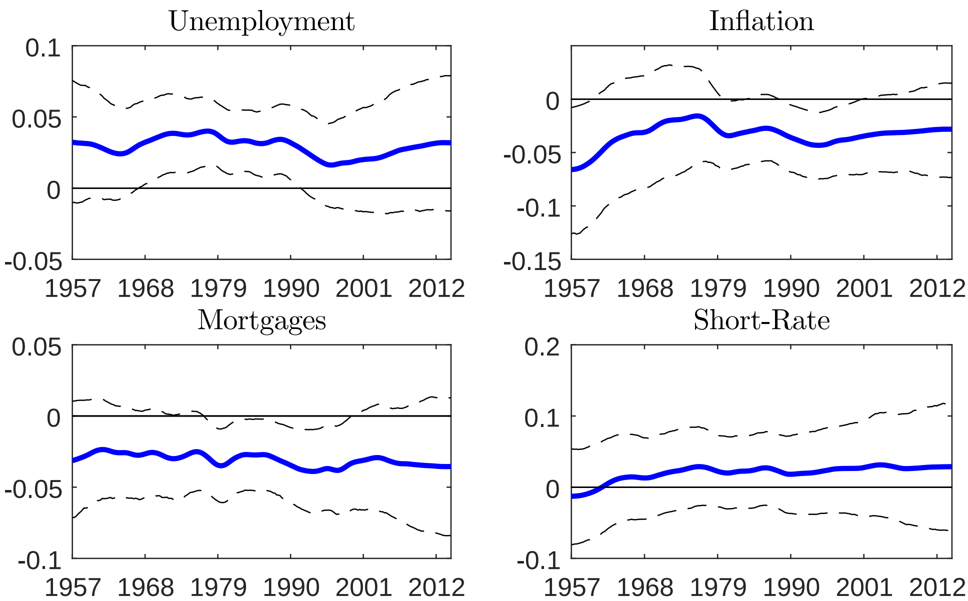


Figure 1.7: Responses to a monetary policy shock after 16 quarters.

Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (gray-dashed) to an initial monetary policy shock of 25bp after 16 quarters.

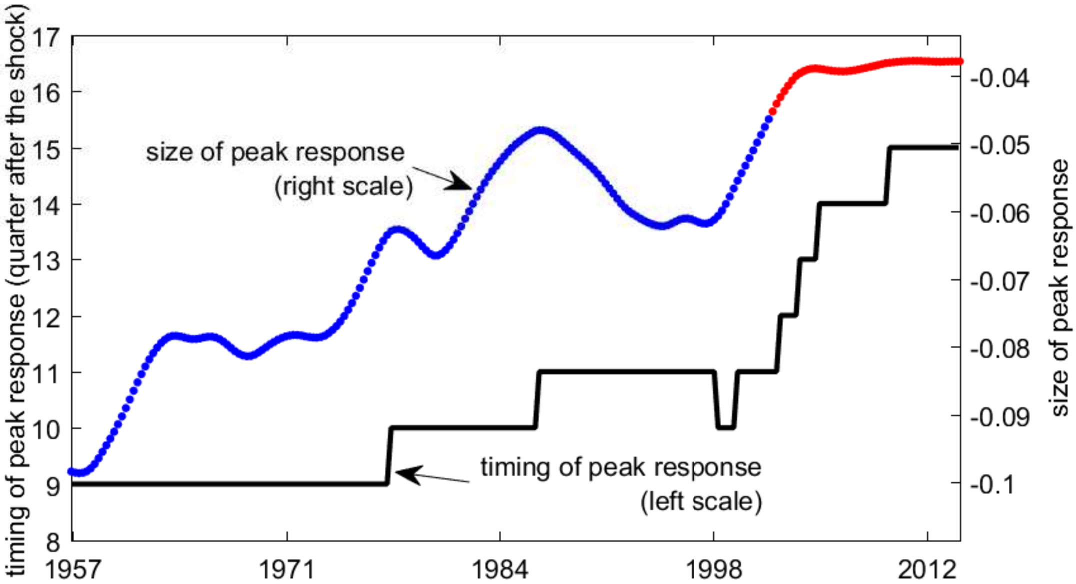


Figure 1.8: Peak response of mortgage debt.

Notes: The peak response of mortgage debt for which the zero line does not lie within the confidence band is shown as a series of blue dots (right axis). The dots turn red when the zero line lies in the confidence band. The black line (left scale) reports the period after the shock in which the peak response occurs.

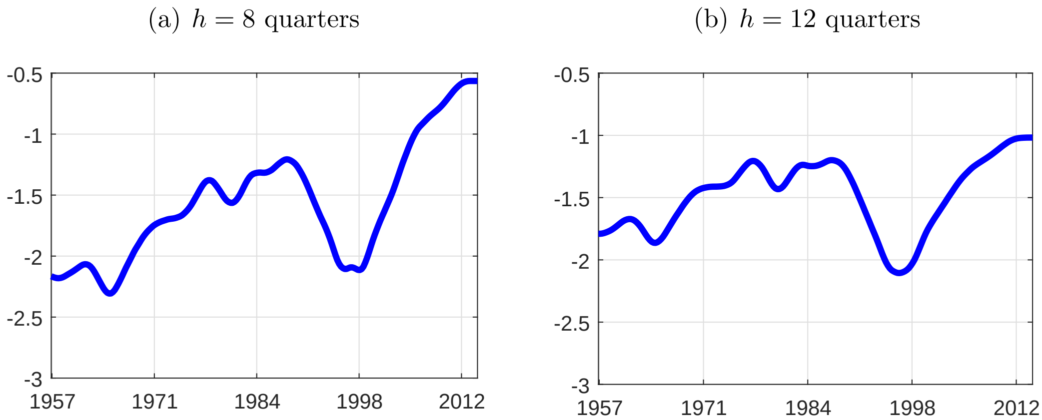


Figure 1.9: Costs of debt reduction in terms of employment.

Notes: The graphs plot the ratio Γ_t over time. Γ_t is constructed as the ratio of the cumulative mean responses of mortgage debt and unemployment for horizon h.

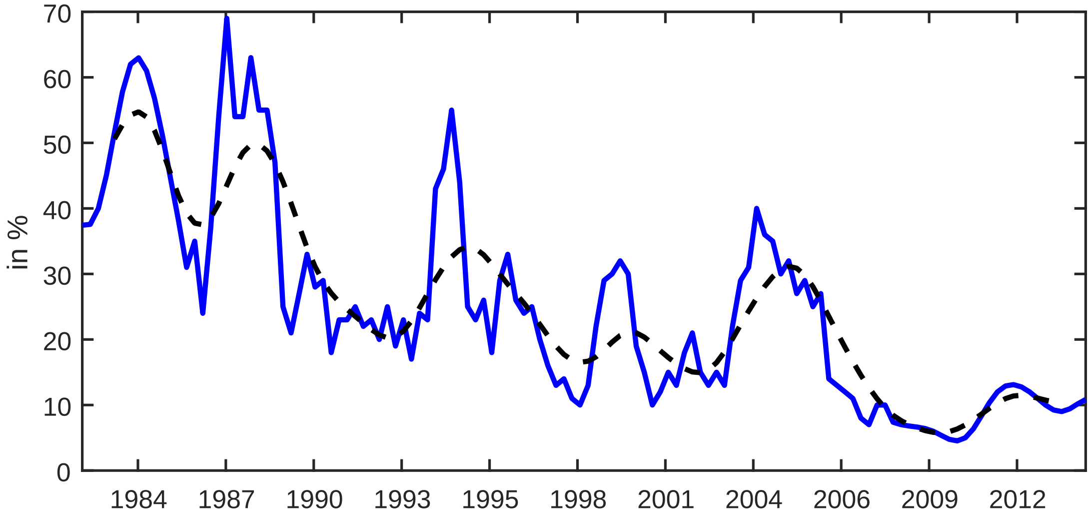


Figure 1.10: Share of adjustable-rate mortgage contracts on overall mortgage contracts.

Notes: The data is taken from the Federal Housing Agency, Monthly Interest Rate Survey, Tab. 9 and 17. We use chained data based on data availability, thus we use from 1982Q2 until 1984Q4 and from 2008Q4 until 2014Q3 interpolated data extracted from annual basis and end-of-quarter monthly data else. The blue-solid path corresponds to the quarterly ARM share, the black-dashed path to its two-year moving average, respectively.

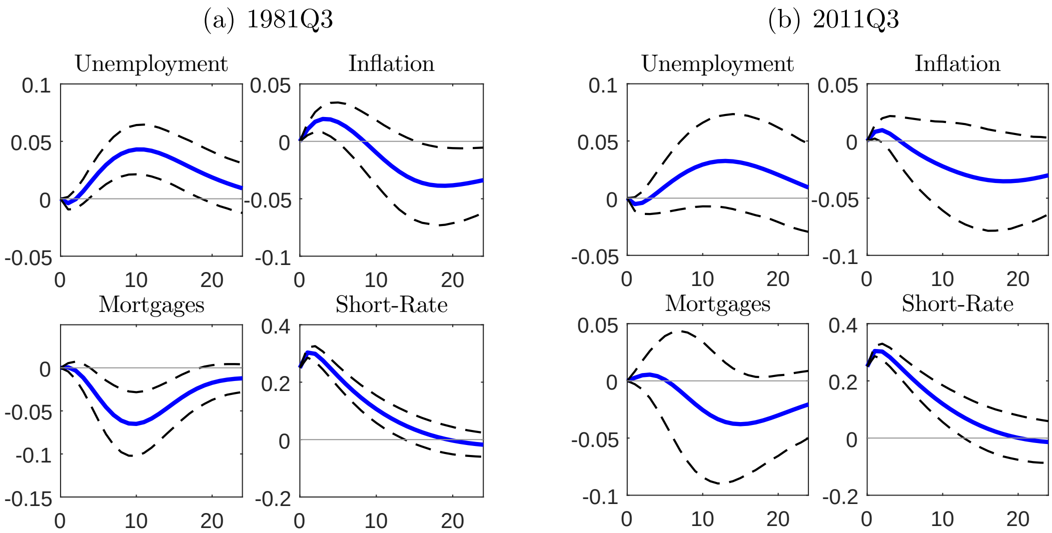


Figure 1.11: Responses to a monetary policy shock in 1983Q1 and 2011Q3.

Notes: Mean response (blue-solid) and 16^{th} and 84^{th} percentiles (gray-dashed) to a monetary policy shock in 1983Q1 (a) and 2011Q3 (b).

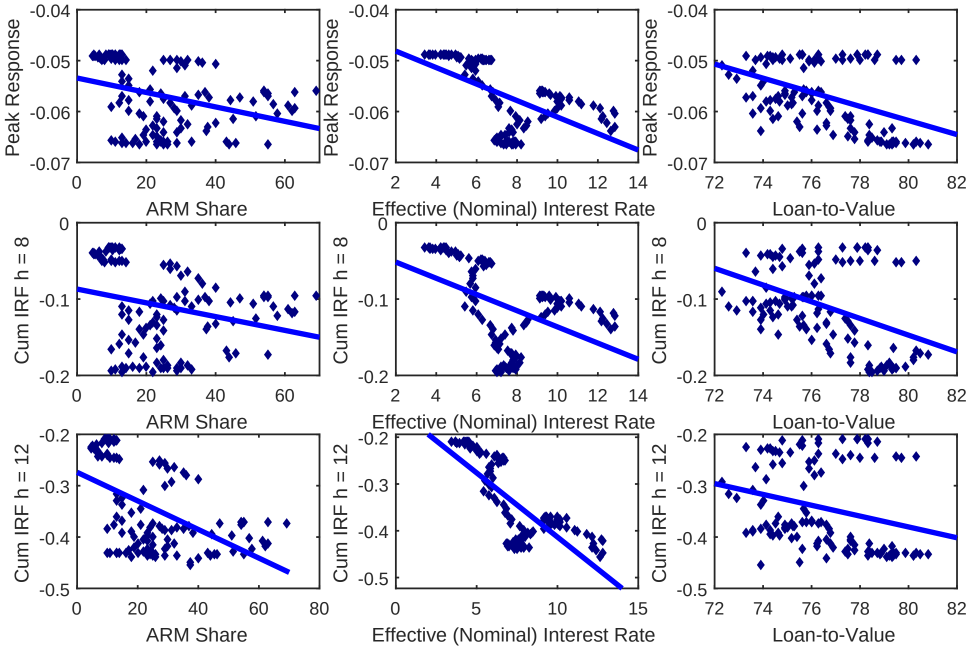


Figure 1.12: Scatter plots, correlation between impulse responses and selected variables.

Notes: Correlation between impulse responses and selected variables. The first row plots the peak responses against these variables, the second (third) row plots cumulative responses with h=8 (h=12) against them.

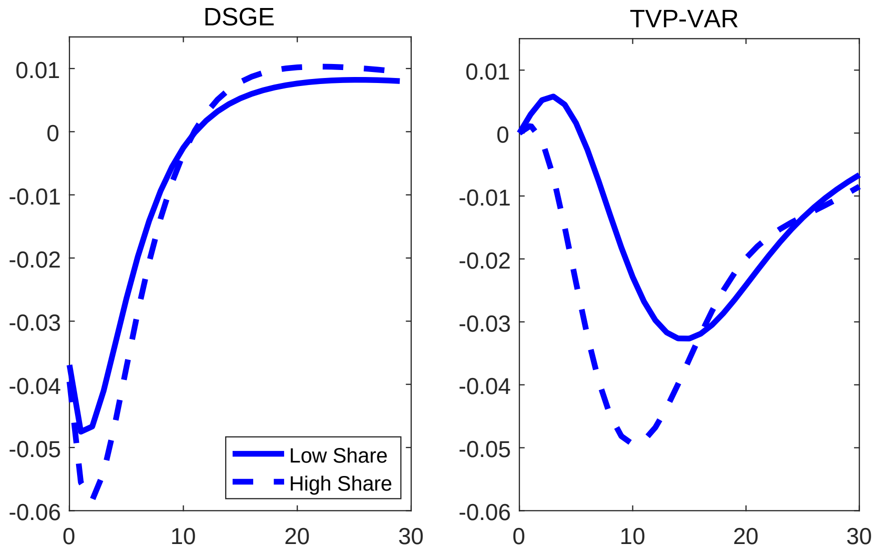


Figure 1.13: Responses of mortgage debt to a monetary policy shock in the DSGE model and the TVP-VAR.

Notes: In both cases, the shock is a surprise increase in the interest rate by 25bp. The DSGE model of Alpanda and Zubairy [2] is calibrated to a 'high share' state with an ARM share of 60% and a 'low share' state with an ARM share of 10%.

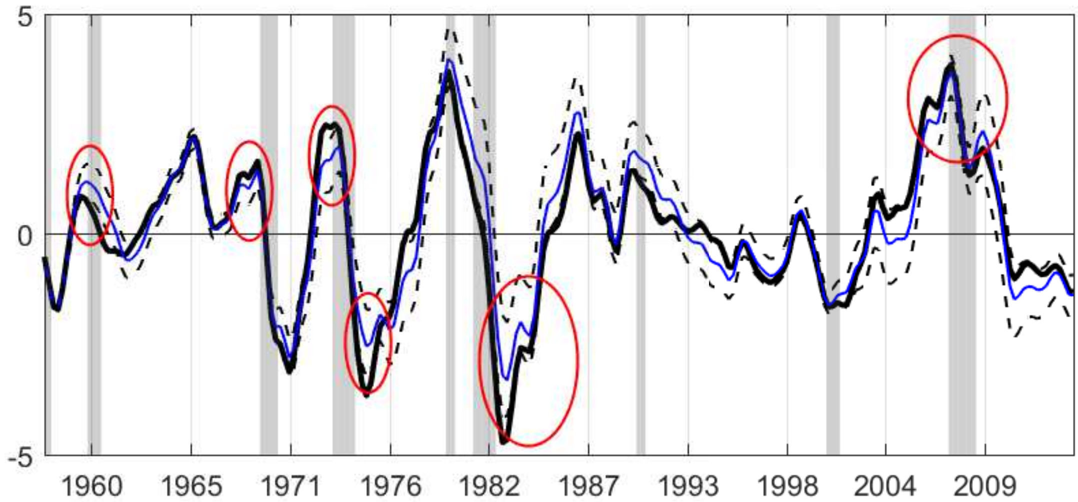


Figure 1.14: Counterfactual analysis: experiment one. Contribution of monetary policy shocks.

Notes: The blue-solid line corresponds to the simulated paths, the black solid line to the actual (observed) data, the black-dotted paths to the 16^{th} and 84^{th} percentiles.

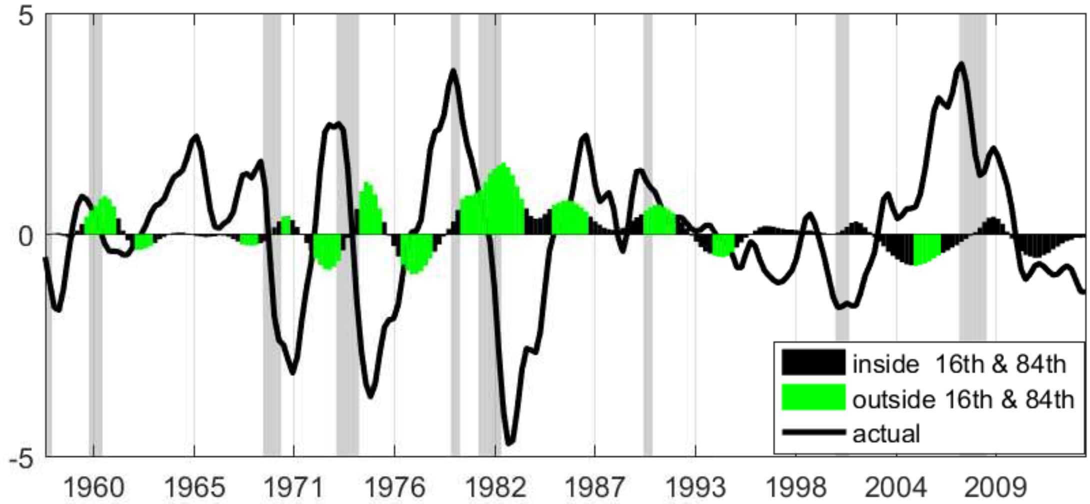


Figure 1.15: Explanatory power of monetary policy shocks for mortgage debt.
Notes: Difference between the counterfactual and the actual path. Black bars indicate that the observable series lies inside the percentiles around the counterfactuals. Green bars indicate episodes where the observable series lies outside the percentiles.

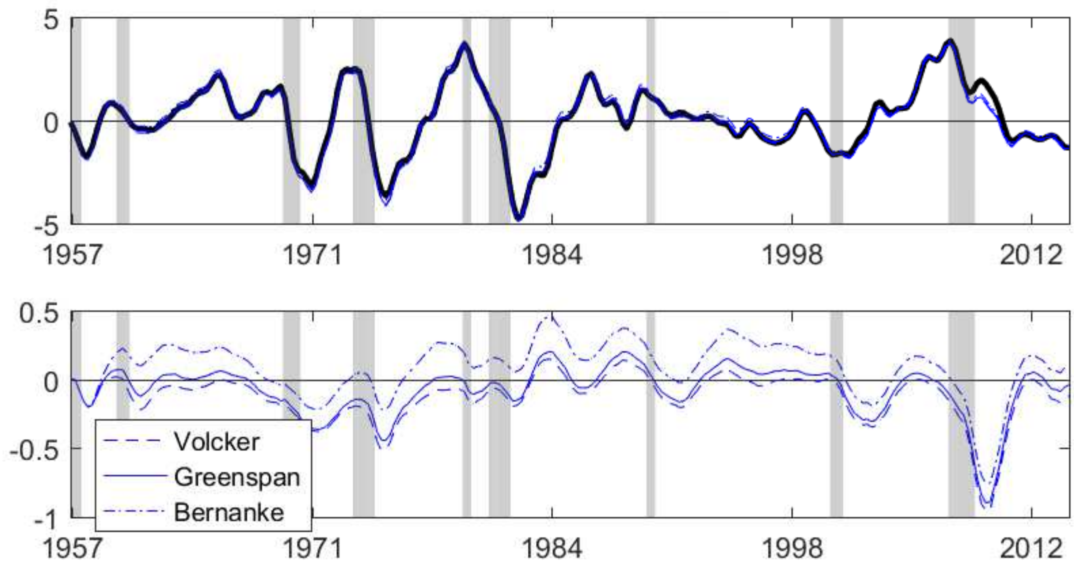


Figure 1.16: Counterfactual analysis: experiment two. Paths of mortgages for different policy rules.
Notes: The upper panel shows counterfactual paths of mortgages for alternative policy rules associated with different Fed chairs. The lower panel shows the differences between the simulated and the actual path.

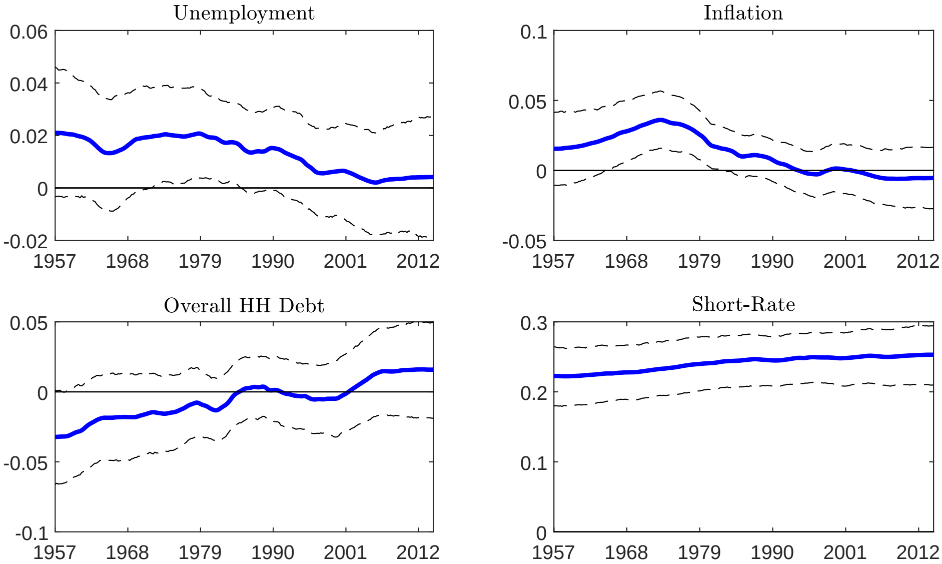


Figure 1.17: Response to a monetary policy shock after 4 quarters: overall household debt.

Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (gray-dashed) to an initial monetary policy shock of 25bp after 4 quarter.

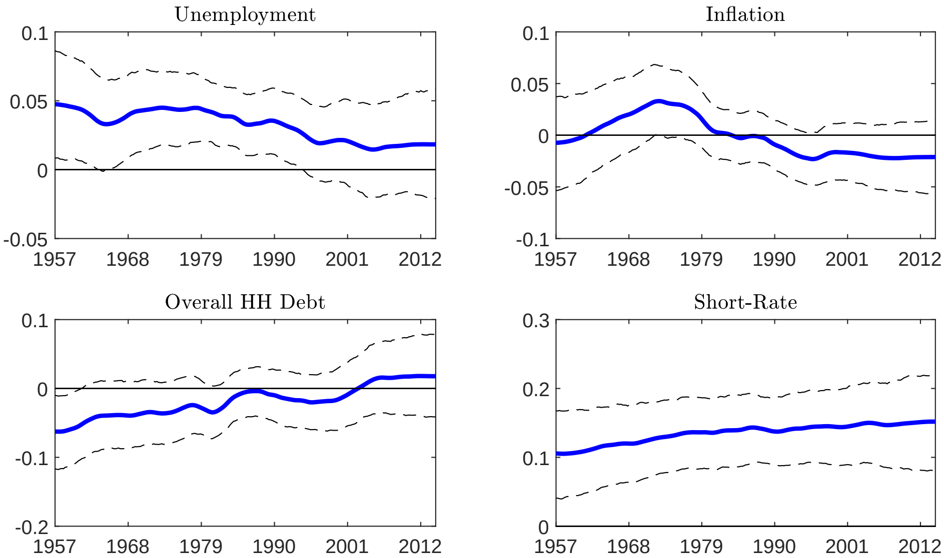


Figure 1.18: Response to a monetary policy shock after 8 quarters: overall household debt.

Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (gray-dashed) to an initial monetary policy shock of 25bp after 8 quarter.

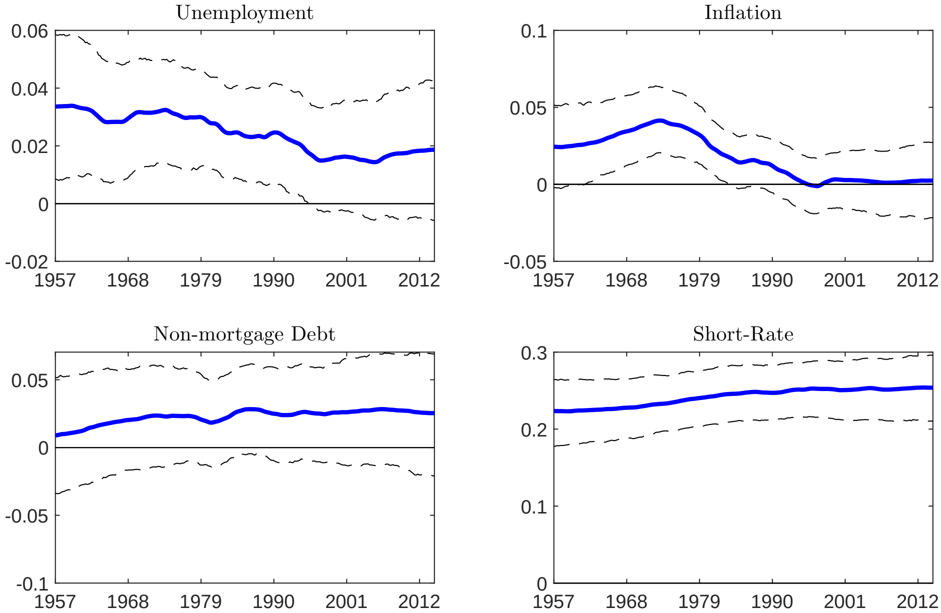


Figure 1.19: Response to a monetary policy shock after 4 quarters: non-mortgages.
Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (gray-dashed) to an initial monetary policy shock of 25bp after 4 quarter.

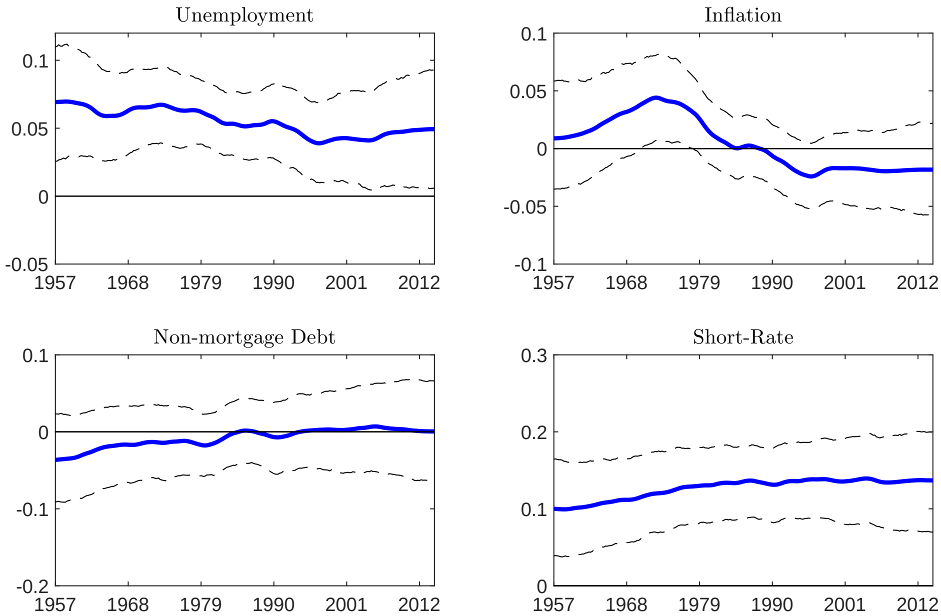


Figure 1.20: Response to a monetary policy shock after 8 quarters: non-mortgages.
Notes: Mean response (blue-solid), 16^{th} and 84^{th} percentiles (gray-dashed) to an initial monetary policy shock of 25bp after 8 quarter.

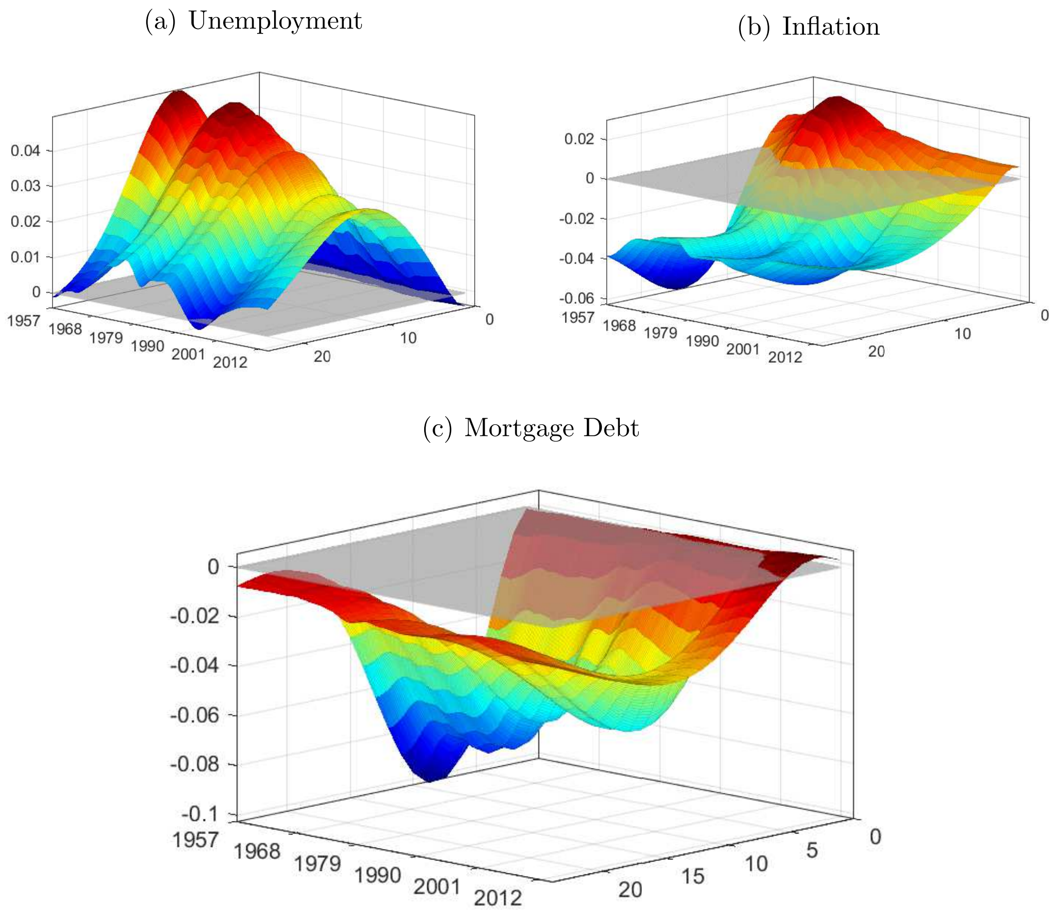


Figure 1.21: Mean Response to a monetary policy shock: unrestricted policy rule.
Notes: Impulse response functions following a 25bp monetary policy shock derived from the TVP-VAR model with an unrestricted policy rule.

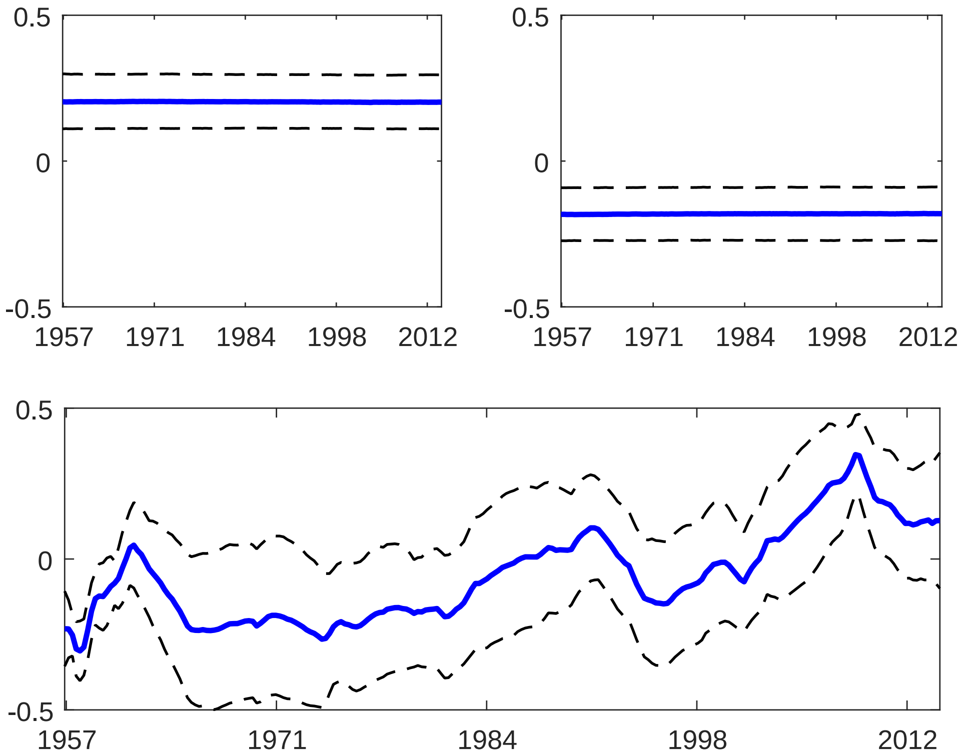
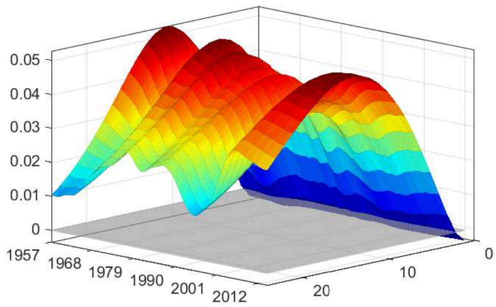


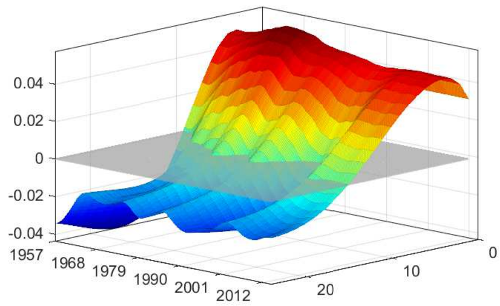
Figure 1.22: Parameter restrictions: policy rule.

Notes: Restricted parameters (blue-solid line) with 16^{th} and 84^{th} percentiles over time. Up right corresponds to b_1^{di}, up left to b_2^{di} and bottom to $\tilde{a}^{di}$.

(a) Unemployment



(b) CPI Inflation



(c) Mortgage Debt

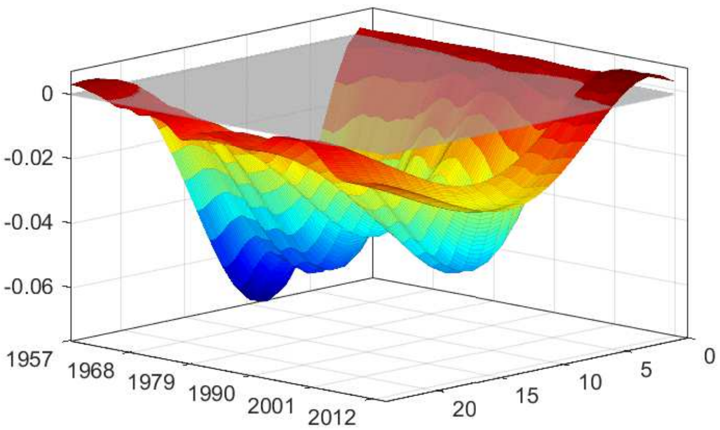


Figure 1.23: Response to a monetary policy shock: alternative variables.
Notes: Impulse response functions following a 25bp monetary policy shock derived from the TVP-VAR model with unemployment and CPI inflation.

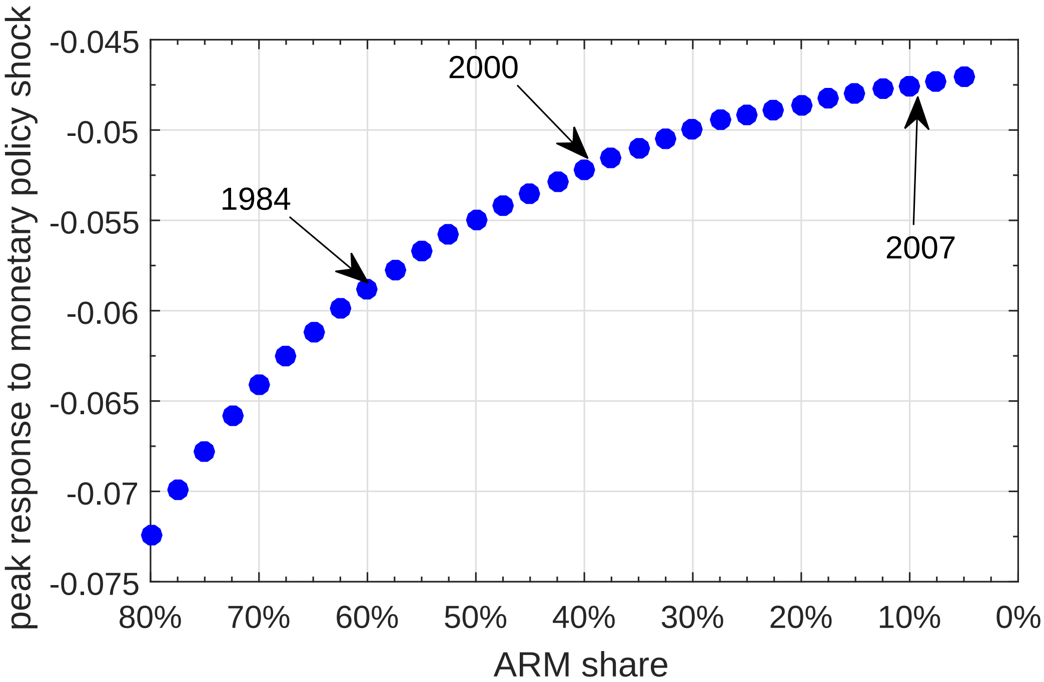


Figure 1.24: DSGE model implied peak responses to monetary policy shocks.
Notes: Each point reflects a DSGE model with an altered ARM share and the corresponding peak response to a 25bp monetary policy shock. Additionally, the graphic is augmented with three selected dates characterized by different ARM shares.

	peak responses			
constant	-0.053^{***}	-0.047^{***}	0.063^{**}	0.075^{**}
	(0.003)	(0.003)	(0.030)	(0.031)
ARM share	-0.139^{*}	-0.737^{***}	-0.699^{***}	-0.352^{*}
	(0.071)	(0.258)	(0.214)	(0.182)
ARM share squared		0.009^{**}	0.008^{***}	0.006^{***}
		(0.004)	(0.003)	(0.002)
LTV			-0.144^{***}	-0.150^{***}
			(0.042)	(0.041)
effective rate				-0.187^{**}
				(0.047)
adj. R^2	0.108	0.254	0.457	0.629

	cumulative responses ($h = 8$)			
constant	-0.087	-0.026	0.814^{**}	0.893^{**}
	(0.134)	(0.055)	(0.413)	(0.439)
ARM share	-0.869	-6.270	-5.974^{**}	-3.714
	(2.229)	(3.846)	(2.703)	(2.520)
ARM share squared		0.084	0.078^{**}	0.063^{**}
		(0.059)	(0.033)	(0.029)
effective rate			-1.000^{*}	-1.142^{*}
			(0.586)	(0.597)
effective rate				-1.221^{*}
				(0.649)
adj. R^2	0.057	0.229	0.398	0.500

	cumulative responses ($h = 12$)			
constant	-0.274^{***}	-0.188^{***}	0.705^{**}	0.885^{**}
	(0.0353)	(0.039)	(0.347)	(0.352)
ARM share	-2.723^{***}	-10.248	-9.933^{***}	-4.787^{**}
	(0.866)	(3.016)	(2.722)	(2.015)
ARM share squared		0.117^{***}	0.111^{***}	0.077^{***}
		(0.421)	(0.0375)	(0.025)
LTV			-1.170^{**}	-1.265^{***}
			(0.482)	(0.466)
effective rate				-2.781^{***}
				(0.561)
adj. R^2	0.264	0.396	0.473	0.701

Table 1.2: Regression of the time-varying policy impact on ARM share.

Notes: The table reports the regression results discussed in section (1.5.1) for various estimation setups. The coefficients on the ARM share and the squared ARM share are multiplied by 10^3. The coefficients on the the LTV and the effective rate are multiplied by 10^2. HAC standard errors are given in parenthesis. ***, **, and * indicate 99%, 95% ,and 90% significance levels, respectively.

2 Unconventional Monetary Policy and Bank Risk-Taking in the Euro Area

This is the author's latest version of the paper that has been revised to take referee reports into account after submitting it to *Contempouranous Economic Policy.* A former version of this paper is available under

Schmidt, J. [2018]: 'Unconventional Monetary Policy and Bank Risk-Taking in the Euro Area', *MAGKS Joint Discussion Paper Series in Economics*, 24-2018.
http://hdl.handle.net/10419/200680.

This paper, including earlier and alternative versions, was presented at the following international conferences[1]:

I. Western Economic Association International (WEAI):
93rd Annual Conference, 06/2018, Vancouver, Canada.

II. Money, Macro and Finance Research Group (MMF):
49th Annual Conference, 09/2017, London, United Kingdom.

III. European Economics and Finance Society(EEFS):
16th Annual Conference, 06/2017, Ljubljana, Slovenia.

IV. Center for European Studies (CEUS):
13th Workshop: Issues of EU Economic Integration 60 Years after the Signing of the Treaty of Rome, 05/2017, Vallendar, Germany.

[1]We thank participants of 13^{th} Center for European Studies Workshop, 16^{th} Annual Conference of the European Economics and Finance Society, 49^{th} Annual Conference of the Money, Macro and Finance Research Group, and 93^{rd} Annual Conference of the Western Economic Association International for fruitful hints and discussions.
Additionally, we want to thank the Frankfurter Institut für Risikomanagement und Regulierung (FIRM) for promoting our research project 'Bank Risk−Taking and Unconventional Monetary Policy'.

Unconventional Monetary Policy and Bank Risk-Taking in the Euro Area

Jörg Schmidt[*,1]

This paper studies risk-taking by European banks. After an overview of the banking landscape in the euro area, we construct a measure of risk-taking that relates changes in three-month-ahead expected credit standards for several non-financial private sector categories to the risk of the macroeconomic environment banks operate in. With this approach, we want to tackle the question if credit standards react disproportionately strong to changes in the monetary policy stance. We use an estimated bond-market-based measure to assess the overall riskiness prevailing in the economy. We want to shed some light on whether banks act excessively risky and provide new evidence as well as an alternative assessment on the amplifying nature of the risk-taking channel of monetary policy. We put our measure into a VAR model in which structural innovations are identified with sign restrictions. The key outcomes of this paper are the following. Expansionary monetary policy shocks decrease our measure of risk-taking. Decreases in our measure are caused by disproportionately strong reactions in credit standards compared to the overall macroeconomic risk, especially since the recent financial crisis. Disproportionately in the sense that our macroeconomic risk measure is less affected by expansionary monetary policy shocks than credit standards. The credit granting reaction depends on the category: In general, loans to non-financial corporations are less sensitive to monetary policy shocks while mortgages seem to be affected more. We conclude that expansionary monetary policy shifts the portfolio of banks to overall riskier asset holdings.

Keywords: monetary policy, euro area, bank risk-taking, credit standards

JEL classification: E44, E52, G12

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2.1 Motivation and Contribution

Problems related to risk-taking in the financial sector have in general gained growing attention since Rajan [17] has introduced this topic and all the more since the Financial Crisis with its deep turmoils in financial markets as well as in the real economy. Borio and Zhu [7] emphasize the importance of the relatively new risk-taking channel of monetary policy for policy makers. Besides lacking a clear and precise definition of the phenomenon *'risk-taking'* by financial intermediaries, they line out that there are multiple forms and dimensions of risk-taking, linked to the behavior and incentives of financial intermediaries. Overall, risk can occur on the funding side, it can be related to securitization activities, misdirected incentives based on principal-agent problems and payment contracts, or the inherent riskiness of financial intermediaries' portfolio of assets, especially loans. In this paper, we focus on the last-mentioned dimension of risk-taking: the ex-ante assessment of the riskiness of additionally acquired assets, here newly granted loans, is in the focal point. To capture this issue, recent literature emphasizes the importance of credit standard adjustments. Ciccarelli et al. [8] assess their importance for monetary policy transmission, both for the US and the euro area. The major results relevant for this paper are that credit standard changes are an important transmitter and amplifier of monetary policy in the euro area, especially for mortgages and corporate loans. They are reduced when banks are in an expansionary monetary policy environment. Similar results are lined out by Paligorova and Santos [16] who focus on individual data of banks' credit-granting decisions. They also use a survey-based measure of risk appetite that stems from the Senior Loan Officer Survey (SLOOS) and show that loan spreads, a measure for the riskiness of individual loans, become relatively lower for banks with higher risk appetite in periods of monetary easing. One important finding, especially for this paper, is that bond investors do not show similar increases in risk appetite during prolonged periods of low interest rates.

From these findings of the existence and operating principles of the risk-taking channel, we deduct the question if the adjustment of credit standards and the overall inherent risk of banks' core business appropriately react to monetary policy shocks. Maddaloni and Peydro [14] work out that the reaction of credit standards to changes in the stance of monetary policy is quite heterogeneous across the euro area. Additionally, they find that especially within mortgage credit standards excessive risk-taking occurs, conditional that banks operate in a low interest rate environment. In their paper, they capture the excessive nature of these adjustments by controlling credit standard changes for altered borrower quality, bank capitalization, or yield changes. They emphasize the importance of these findings for the risk assessment of the overall financial system, but they also line out that identifying *"excessive risk-taking"* remains a difficult issue. This is where we want to contribute. We relate the adjustments in credit standards to the macroeconomic environment banks operate in and focus on the reaction to changes in the monetary policy stance. If they do not adjust adequately, potential pitfalls for the financial system in general and bank balance sheets in particular might stem from disproportionately strong credit standard adjustments, induced by changes in monetary policy.

We suggest an alternative way to think about the amplifying nature of monetary policy transmission via the risk-taking channel. We bring in the aspect of disproportionately strongly altered credit standards by financial intermediaries. In contrast to the existing literature, we want to evaluate changes in credit standards for the non-financial private sector with a measure extracted from their financial market substitutes: corporate bonds. The advantage of using bond markets is that they explicitly reflect the broad view of markets regarding the riskiness of the respective bonds, conditional on the set of perceived current and future macroeconomic risk. This market-view reflects the default probabilities of bonds and displays the perceived riskiness of these financial substitutes, as these default probabilities highly depend on business-cycle fluctuations.

The tight relationship between business cycle fluctuations and various bond market spreads is a well known one. Gilchrist and Zakrajšek [12] use a broad spectrum of US corporate bond prices to construct an economic forecasting index for the US economy. They show that bond spreads have high explanatory power for the present as well as future macroeconomic risk. This holds especially for term premia and idiosyncratic risk premia, which are related to expected future short-rates and to changes in the probability to default of corporations, respectively. Thus, these premia are very useful to evaluate prevailing and future macroeconomic risks. For the euro area, Gilchrist and Mojon [11] introduce a similar measure by using bond market spreads. They construct risk indicators that reflect the refinancing costs for financial as well as non-financial private sector firms via the discrepancy of their respective bond yields to German Bund, the assumed risk-free rate. Adrian, Moench and Shin [2] construct a macro risk premium (MRP, hereinafter), an idea we will rely on later. It is based on bond market information to connect the in principle unobservable tension of Value-at-Risk constrained bank balances and their respective portfolio of loans with their propensity to grant credit. They interpret the resulting series as a proxy for the marginal propensity to grant additional credit and elucidate that this proxy is a market-based view of the ease of banks' credit standards. We will pick up all these ideas later in this paper.

Linking credit standard survey responses to macroeconomic and other financial variables is not a new approach but is done e.g. in Bassett et al. [6]. They introduce a credit-supply indicator for commercial and industrial loans that corrects the individual responses of US SLOOS credit standard changes for bank-specific and macroeconomic factors. Next, they include this indicator into a VAR model that consists of real GDP, inflation, lending capacity, and the bond spread index by Gilchrist and Zakrajšek [12]. A major outcome is that negative[1] shocks to their credit-supply indicator induces a lower GDP and a negative borrowing capacity reaction as well as increased bond premia. They also find that these supply-dampening shocks cause a monetary easing. Likewise, Altavilla et al. [4] proceed for the euro area. They construct a propensity-score-based loan supply indicator that matches the individual Bank Lending Survey (BLS, hereinafter) responses queried by the ECB and other bank-specific information. Within a VAR model, they show that tightening in credit standards leads non-financial corporations to evade bank loans and increase funding via issuing additional bonds. This emphasizes the interchangeability of both kinds of debt capital. We combine different aspects and ideas of the presented literature to tackle the issue of evaluating ex-ante risk-taking of euro area banks in the context of monetary policy shocks.

This paper proceeds as follows. We present some facts and simplistic regressions about European banks' operational business and about the nexus between credit standards, bank profitability, and unconventional monetary policy. We then estimate a measure for the macroeconomic risk perceived by financial markets. For this purpose, we construct a measure that reflects the degree of riskiness of the macroeconomic environment by using information extracted from European bond markets. We then relate credit standard changes to this measure of macroeconomic risk. With this approach, we try to elaborate in how far, for instance, monetary policy shocks drive numerator and denominator of this ratio in the same manner or if they show differences. If they do so, this can be an indicator of risk-taking. We also account for the various non-financial sector categories queried in the BLS and explicitly distinguish between credit standards for non-financial private corporations, loans for house purchases[2], and consumer credits. We also calculate an overall non-financial private sector credit standard. This results in four different Relative

[1] In the sense of supply-dampening.

[2] We will use the phrases 'mortgages' and 'loans for house purchases' interchangeably within this paper. Rubio [19] provides a deeper look at the housing market heterogeneity in the euro area and differences in the contract and loan-rate structure, but in most countries mortgage contracts dominate housing finance.

Risk-Taking Measures. We then put each of these measures into a VAR model that consists of GDP-growth, consumer price inflation, a monetary policy variable, and credit growth of the respective category. For identification, we use sign restrictions. The subsequent structural analysis with impulse response functions to a monetary policy shock is a proper way to figure out in how far the included variables and especially our ratio as well as credit growth react to unexpected changes in the monetary policy stance. We use two samples to account for possible differences related to unconventional monetary usage. The key outcome is that credit standards indeed react disproportionately strong to monetary policy shocks in general and most intense in the sample characterized by the usage of unconventional monetary policy measures. This can be observed for three out of the four categories we deal with in this paper, most pronounced for mortgages. One additional point worth to mention is that expansionary monetary policy shocks do often not stimulate credit growth. Last, these outcomes are tested for robustness with an alternative identification scheme. We exploit the recursive ordering of the variables, applying a lower-triangular cholesky decomposition.

2.2 Banking in the Euro Area

2.2.1 Euro Area Banks' Lending Activities

The three most relevant non-financial private sector categories, and the ones queried in the BLS when credit standards are of interest, are loans to non-financial corporations, loans for housing, and consumer credit. Fig. (2.1) depicts their respective share on the outstanding amount of loans of these categories, calculated using the outstanding stock of loans that is depicted in Fig. (2.10), appendix. As we can see, loans for non-financial corporations and loans for housing are by far the most relevant business areas, while consumer credit plays a minor role in the European banking landscape. One interesting thing worth to point out is that since the peak of the Financial Crisis the share of loans for housing slowly but steadily increases, mirror-imaging the persistently decreasing share of loans to firms.[3]

Turning to banks' profitability, we see some interesting facts. Besides shifts in the share of business activities, financial as well as sovereign debt crises, financial market turmoils and unconventional monetary policy measures to an extent never seen before, European banks have been able to keep the profitability of their core business, credit granting to the non-financial private sector, relatively stable. Fig. (2.2)

[3]This shift in business activity might be related to the overall increasing engagement in real estate markets across Europe, especially since the most recent financial crisis.

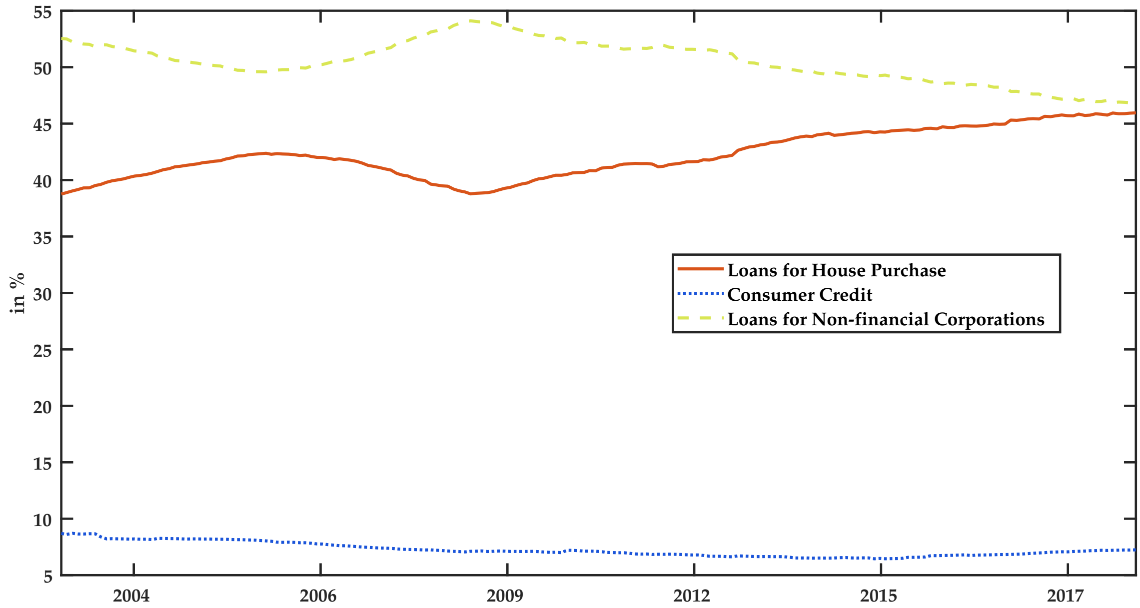

Figure 2.1: Shares of the three non-financial private sector credit categories queried in the BLS, on the overall outstanding amount of non-financial private sector loans.
Notes: Non-financial corporation loans (yellow-dashed), Mortgages (red-solid), and Consumer Credits (blue-dashed).
Source: Author's calculations.

depicts the average net margins of European banks, a proxy for their profitability.[4] This holds for outstanding as well as for newly granted loans. The net margin for new loans fluctuates tightly around 1.5% and the gap between margins of outstanding and new loans vanishes since the Financial Crisis.[5] The ability to ensure constant margins, especially for newly granted loans, might root in fluctuations in risk-taking by European banks. As outlined in the introduction, this risk-taking channel of monetary policy primarily works via adjusting credit standards. One key characteristic of banks, in contrast to e.g. bond investors, is that they work with leverage on their equity. To maximize their profits, banks have the propensity to adjust their leverage to work at a minimum Value-at-Risk constraint that is set by their supervisors. Adrian and Shin [3] elaborate that banks strife to employ all additional scope of leverage when their equity faces e.g. a positive valuation shock after expansionary monetary policy. This finally results in extending the credit supply to less credit-worthy borrowers via lowering their credit standards. As a result, this lowering works as an additional amplifier that augments the traditional bank lending channel and further speeds up the financial accelerator in the transmission

[4]A net margin is the difference between interest rate earnings and funding costs.
[5]This seemingly closing gap might be a relic from pre-euro times with old credit contracts, that stem from the heterogeneous landscape then, expiring.

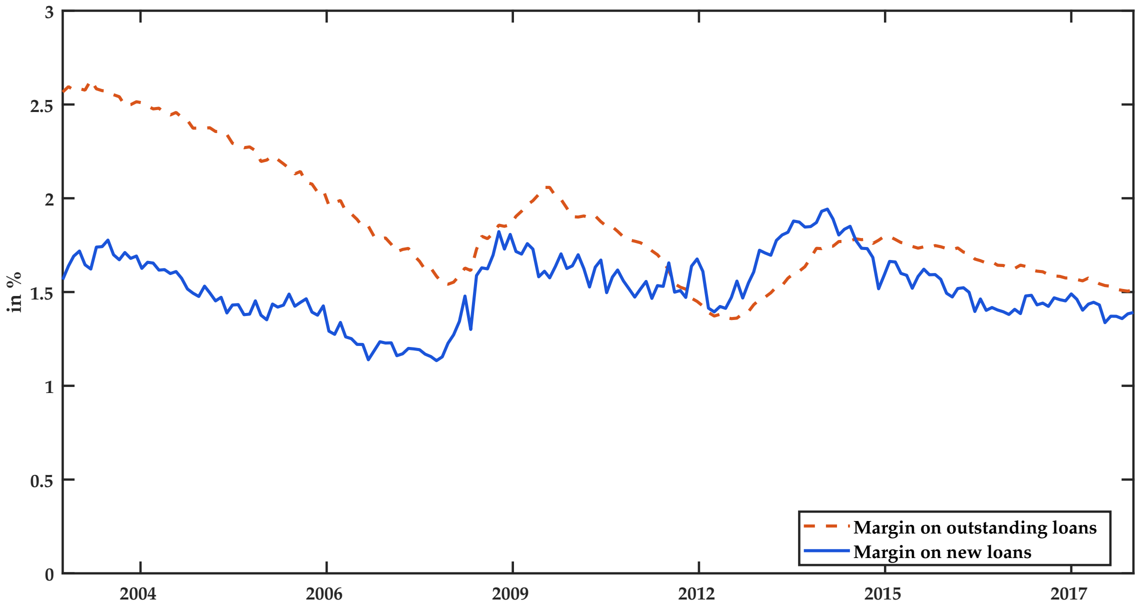

Figure 2.2: Average euro area net bank margins for outstanding and newly granted loans.
Notes: For simplicity, the average margins depicted here are calculated by multiplying national bank margins with their respective share on the weighting of the HICP. Source: ECB Statistical Data Warehouse, author's calculations.

of monetary policy.

As the European financial system is dominated by banks, their importance to provide capital for firms is high, making them the major player in these mechanisms. Thus, in the following, we will take a closer look at their credit standard adjustments in the euro area to get a better understanding of what is meant by credit standards within this paper and how these standards have evolved.

2.2.2 Credit Standards in the Euro Area

The ECB quarterly conducts the BLS among the largest banks in the euro area since 2003. This survey inter alia contains questions about *expected changes* in the applied credit standards for the next three months. The survey distinguishes between three different non-financial private sector categories outlined before. Questions eight and 21 of the survey, see Fig. (2.11) in the appendix, are the focal point of interest in this paper. Unfortunately, the complete survey results for all 140 survey participants are not available due to the confidential nature of the questionnaire. Thus, we unfortunately can not take into account individual bank characteristics. Furthermore, the *level* of credit standards is, in contrast to e.g. the US SLOOS, not available, only *net-percentage changes* are published.[6] As shown in Eq. (2.1), we also construct an overall non-financial private sector credit standard net-percentage change, CS_{NFPS}, by using the weightings (w_i) depicted in Fig. (2.1):

$$CS_{NFPS,t} = \sum_{i=1}^{3} w_{i,t}\ CS_{i,t}, \tag{2.1}$$

with $i = \in$ {non-financial corporations, mortgages, consumer credit}.
Fig. (2.3) depicts the raw data of the net-percentage changes in the relevant questions of the ECB's BLS, augmented with our overall non-financial private sector credit standard changes.[7]

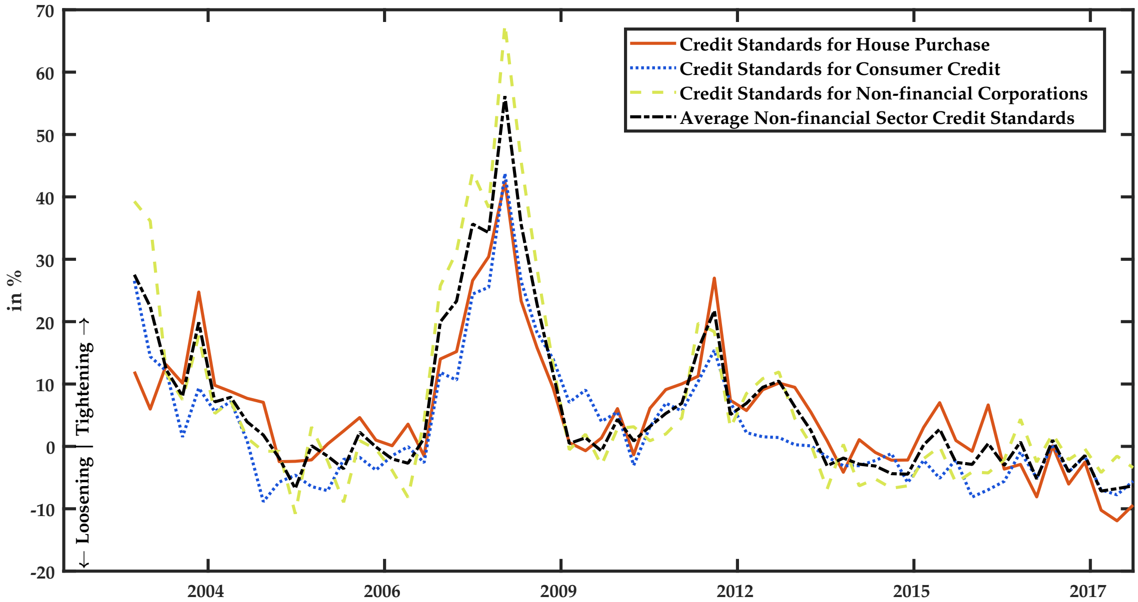

Figure 2.3: Net-percentage changes in credit standards in the euro area.
Notes: Average non-financial Sector credit standards (black-dashed), Non-financial corporation credit standards (yellow-dashed), Mortgage standards (red-solid), Consumer Credit standards (blue-dotted).
Source: ECB Statistical Data Warehouse, author's calculations.

Per construction, the range of possible outcomes of the net-percentage changes is

[6] In the context of credit standards, the net-percentage change is defined as the difference between the sum of the percentages of banks responding "tightened considerably" and "tightened somewhat", and the sum of the percentages of banks responding "eased considerably" and "eased somewhat".

[7] We do not want to conceal that there might be a systematic bias in the answers of survey participants. As the ECB, is also the participants' supervisory authority via the Single Supervisory Mechanism, banks might have an incentive to understate their intended alignment of credit standard policies, at least since November 2014. This could bear the caveat of a bias when answering the survey. This bias is directed upwards because banks maybe want to understate their true intended credit standard adjustments. We leave this issue for further research.

bounded to $[-100; 100]$.[8] The course of the European economy with its outstanding events is quite well mirror-imaged by the series. The echo of the busted new economy bubble, the Financial Crisis, and the European Sovereign Debt Crisis are peaks in credit standard tightening episodes, while before the Financial Crisis and after the ECB announcement of possible Outright Monetary Transactions (OMT) credit standards show the tendency to loosen. In the next subsection, we want to look at the nexus between quite volatile credit standard changes and banks' relatively stable profitability.

2.2.3 Credit Standards and Bank Profitability: Who drives Whom?

When taking a first glance on possible empirical relationships between credit standards and banks' margins, we can neither disentangle a clear causal direction nor assume an exogenous relationship. Both variables might be related to each other endogenously:

I. Changes in credit standards can impact banks' margins **or**

II. Efforts to stabilize margins can be directed to credit standards.

We pick up both possible setups. Additionally, we want to take a first, superficial look at how periods of unconventional monetary policy affect credit standards and margins, respectively. To mitigate the possible problem of endogeneity that not only applies to I or II, above, but also to our other variables, we involve lagged values on the right-hand side of the regression equation. We control for the term spread (ts), an important indicator for banks' ability to profitably transform maturities, which is approximated by the difference between 10-year and three-month German Bund yields. Eq. (2.2) reflects setup I we have described above. Furthermore, we include a dummy variable in an alternative modeling to account for the possible effects of unconventional monetary policy. As our focus lies on the ex-ante perspective of the risk-taking of financial intermediaries, we only focus on margins of newly granted loans. This results in the following setup:

$$margin_t = \alpha_1 + \alpha_2 cs_{t-1} + \alpha_3 ts_{t-1} + \alpha_4 UMP_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2)$$
$$\text{with } UMP_t = \begin{cases} 1, & \text{if t} \geq \text{ July, 2012} \\ 0, & \text{otherwise} \end{cases}. \tag{2.2}$$

[8] 100 = all banks tighten their standards (considerably), −100 = all banks ease their standards (considerably).

Modeling the dummy variable this way is motivated by a drastic shift in monetary policy in the euro area: Draghi's "Whatever it takes ..." statement and the announcement of OMT. Since this announcement, the ECB enhanced its toolkit with additional liquidity provision for the financial sector as well as unconventional measures with a stimulating intention. This is motivated by subdued inflation as well as inflation expectations below the ECB's target near but below 2%.

We estimate Eq. (2.2) with two distinct samples: a complete one, starting in 2003Q2 and ending 2018Q3, and a sample that starts 2008Q1, when financial turmoil started, also until 2018Q3. Tab. (2.1) contains the results. As we can see, higher (i.e. tighter) credit standards in general lead to significantly higher bank margins, if we account for our UMP dummy. This overall small effect is weaker in the sample starting in 2008, indicating that the impact of credit standard changes on margins has diminished since the Financial Crisis. As expected, higher term spreads increase the margins significantly as well. Also here, we see a weaker effect compared to the full sample.[9] A third finding stands out. Since the announcement of OMT and Draghi's "Whatever it takes ..." statement, reflected by our dummy variable, we see significant positive effects on banks' margins. One might conclude that European banks' profitability largely benefited from these ECB actions. This interpretation is in line with Szczerbowicz et al. [21] who state that primarily refinancing costs of banks sank drastically after the introduction of various unconventional measures that were directed towards liquidity provision and lowering government bond risk spreads.

The second possible link between credit standard changes and margins, setup II, are efforts to maintain stable margins via credit standard adjustments, as reflected by Eq. (2.3):

$$cs_t = \alpha_1 + \alpha_2 margin_{t-1} + \alpha_3 ts_{t-1} + \alpha_4 UMP_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2)$$
$$\text{with } UMP_t = \begin{cases} 1, & \text{if t} \geq \text{ June, 2012} \\ 0, & \text{otherwise} \end{cases} . \tag{2.3}$$

Tab. (2.2) shows the regression results. A change in the lagged margin only induces in the model without the UMP dummy for the sample beginning in 2008 a significant effect, with a negative sign. A one percentage point increase in the margin lowers (net-percentage change) credit standards by almost 30. Higher margins seem

[9] This might be rooted in the overall lower and less volatile term spread which kept shrinking due to the overall very expansionary monetary policy and the very low interest rates for a prolonged period since 2008.

margin_{new}	2008Q1 - 2018Q3		2003Q2 - 2018Q3	
c	1.45***	1.17***	1.35***	1.18***
	(0.05)	(0.10)	(0.05)	(0.05)
cs (-1)	0.0004	0.007**	0.003*	0.007***
	(0.002)	(0.003)	(0.002)	(0.002)
ts (-1)	0.08**	0.16***	0.12***	0.16***
	(0.03)	(0.04)	(0.03)	(0.02)
UMP (-1)		0.24***		0.23***
		(0.07)		(0.04)
adj. R^2	0.10	0.28	0.22	0.49

Table 2.1: Regression results for Eq. (2.2).
Notes: HAC standard errors in parenthesis. *, **, and *** indicate 90%, 95%, and 99% significance levels.

to go in hand with risk-taking by banks via adjusted credit standards. Interestingly, the effect vanishes within our simplistic setup, if we account for unconventional monetary policy measures. They have in both samples a strong lowering impact on credit standards. We interpret these findings as a hint that since the introduction of unconventional monetary policy the nexus between risk and return might dissolve due to the lowering impact of this policy on credit standards.

We can summarize this small excursion. The margin on new loans is affected by (past) credit standards, the term spread, and unconventional monetary policy. Credit standard changes seem to be primarily driven by the term spread and unconventional monetary policy, not by the margin. We can point out that both seem to be highly impacted by unconventional monetary policy measures: margins are boosted, credit standards are pushed downwards. Unfortunately, with our setup we cannot solve the causal, structural relationship between margins, credit standards, and monetary policy. We refer for a deeper reading to, for instance, Neuenkirch and Nöckel [15] who elaborate within a VAR framework that expansionary monetary policy induces a quick and strong downward adjustment of banks' credit standards, intended to keep margins stable. They line out that, beside heterogeneous rates of success across euro area member states, on average banks' efforts to stabilize their margins seem to work, at the cost of lower credit standards.

The presented results and literature give a superficial idea about the existence of the risk-taking channel, the role credit standards play within it, and how unconventional

$cs_{avg.}$	2008Q1 - 2018Q3		2003Q2 - 2018Q3	
c	56.60**	35.47***	25.86	4.82
	(26.01)	(12.40)	(23.84)	(18.20)
margin (-1)	-29.91**	-2.15	-10.19	12.07
	(14.62)	(8.18)	(14.70)	(10.63)
ts (-1)	-2.91	-10.30***	-3.40	-8.79***
	(3.33)	(2.22)	(3.69)	(3.44)
UMP (-1)		-21.57***		-15.10***
		(4.26)		(4.49)
adj. R^2	0.23	0.71	0.07	0.34

Table 2.2: Regression results for Eq. (2.3.).
Notes: HAC standard errors in parenthesis. *, **, and *** indicate 90%, 95%, and 99% significance levels.

monetary policy affects this channel. In the following, we continue to pursue our aim: get a measure that relates private sector credit standard adjustments to the prevailing and expected macroeconomic conditions. This helps us to quantify the phenomenon of risk-taking via altered credit standards. Consequently, this can help to answer the question if credit standard changes are adequate. Thus, the following section discusses the construction of our MRP to evaluate the prevailing macroeconomic environment banks operate in.

2.3 Assessing Macroeconomic Risk

The assessment of the macroeconomic conditions is also queried in the BLS, see questions (2c and 11c), summarized in Fig. (2.12), appendix. As it asks for the *perceived* general economic risk *by banks* and its impact on credit standard changes, we do not use this measure for two reasons. First, we want to focus on expected changes, three months ahead, and not past impacts. Second, our focus lies on an assessment of banks' risk-taking based on a market perspective of the overall risk inherent in the economy, not banks' own assessment.

Instead, we pick up the tight connection between bond market spreads and (future) macroeconomic performance, as outlined, for instance, by Favara et al. [10]. They emphasize the ability of various spreads in predicting economic downturns. Especially the slope of the yield curve, a synonym for the term spread, has high informative power about future economic conditions[10]. It reflects the expected future yield environment, conditional on a central bank reaction to future economic circumstances. Various risk premia for a set of corporate bonds with different ratings reflect the default risks that also depend on the current and future macroeconomic environment. A wide-spread measure for this nexus is the excess bond premium (EPB) suggested by Gilchrist and Zakrajšek [12] for the US. They introduce a corporate bond credit spread index based on a rich set of micro-level bond market data and extract this EPB. This premium is independent of idiosyncratic risk components of the underlying bonds. It can be understood as a residual component that captures changes in the overall default risk of the set of underlying bonds. Thus, it reflects the economy-wide risk of corporate bond defaults. For this paper, we pick up these connections in a slightly different manner. We rely on the perspective of Adrian, Moench and Shin [2] who describe, based on former work[11] how to construct a measure, the MRP, that reflects the in principle unobservable tension of banks' balance sheets and thus their propensity to grant additional credit. The tension of bank balances is closely related to the overall macroeconomic conditions because financial intermediaries are confronted with a binding Value-at-Risk constraint and the respective set of their assets, in particular the loan portfolio, continuously face valuation effects. These valuation effects primarily depend on the overall environment they currently operate in.

Adrian, Moench and Shin [2] suggest using bond premia to approximate these unobservable value fluctuations, as bonds and loans are close substitutes for borrowers and thus face similar fluctuations in their value. Within their approach, GDP-growth serves as a measure for current macroeconomic conditions. They regress growth of GDP on a set of US yield spreads, extracted from bond markets. Adrian, Moench and Shin [2] use term and idiosyncratic risk spreads of different corporate bond yield classes that differ by their respective rating. The intention of this approach is that term and risk spreads reflect the view of markets regarding hurdle rates, conditional on the riskiness of these assets. Thus, it reflects how much compensation does a bond investor requires to bear this additional risk inherent in the respective corporate bond. We pick up these ideas and construct a euro area MRP in a similar way. We regress GDP-growth[12] on spreads constructed with the information euro

[10] A point we skipped in the discussion of the previous session for sake of simplicity because we were primarily interested in the transformation of maturities, from the perspective of banks' profitability. For further reading about this nexus, see e.g. Rosenberg and Maurer [18]. They split the term spread into several components linked to expectations about future real rates, inflation, and uncertainty.

[11] Adrian, Estrella and Shin [1] and Adrian and Shin [3].

[12] Using the growth of industrial production does slightly alter the resulting MRP, as it reflects the

area bond markets carry within them, exploiting the high correlation between (future) macroeconomic circumstances and the respective spreads. The term spread, ts^{10Y}, is the same as in Sec. (2.2.3). Various risk premia, rp_i, are constructed by subtracting German BUNDs from a set of European corporate bond yields with the same maturity. Eq. (2.4) depicts this procedure, all variables enter on a quarterly frequency.

$$\begin{aligned} \Delta ln(GDP_t) &= \alpha_1 + \alpha_2 ts_t^{10Y} + \alpha_3 rp_t^{AAA10Y} + \alpha_4 rp_t^{AA10Y} \\ &\quad + \alpha_5 rp_t^{A10Y} + \alpha_6 rp_t^{BBB10Y} + \alpha_7 rp^{high\ yield} + \epsilon_t \\ &\quad \text{with } \epsilon_t \sim N(0, \sigma^2). \end{aligned} \tag{2.4}$$

The resulting coefficients, collected in $\hat{\boldsymbol{\alpha}}$, are then multiplied by the different yields and the constant that we collect in $\mathbf{X}$, which is in turn used in Eq. (2.4) to capture the pure information effect of yields about current macroeconomic conditions. This results in a series that can be interpreted as a market-based assessment of prevailing and expected macroeconomic risk. We deviate in two ways from the approach of Adrian, Moench and Shin [2] First, we do not subtract the mean of the risk spread of the AA-rated corporate bond and divide the resulting time series by the standard deviation of this bond. We explicitly want to exploit the divergence of a vast spectrum of bond yields across the different states of the business cycle. This is reflected by the movement of the underlying series. Thus, we obtain a risk measure that reflects the variety of potential customers[13] banks face instead of a representative, 'one fits all' measure. In addition, we standardize this variable later on for reasons that become clear below. Second, we do not include a short-rate in Eq. (2.4) because we will use the resulting variable later on within a VAR framework that contains a short-rate, namely EONIA.

Since high macroeconomic risk and the resulting spreads are linked to low or negative economic growth and especially low or negative term spreads are linked to high future macroeconomic risk, the estimated coefficients here enter the MRP estimation negatively. Eq. (2.5) reflects our approach.

$$\widehat{MRP} = -\mathbf{X}\hat{\boldsymbol{\alpha}}' \tag{2.5}$$

Fig. (2.4) plots the resulting MRP and, for the ease of interpretation, euro area

more volatile part of the business cycle. Besides that, the results remain qualitatively similar and are available upon request.

[13]Keep in mind that bonds and loans are assumed to be close substitutes.

Figure 2.4: Macro Risk Premium and euro area GDP-growth.
Notes: Macro Risk Premium (red-dotted, left ordinate), quarterly euro area GDP-growth (blue-solid, right ordinate).
Source: Thompson Reuters Datastream, author's calculation.

GDP-growth. Similar to the net-percentage changes of credit standards, the estimated MRP reflects the major pattern of the euro area economy in our sample. We clearly see the deep impact of the Financial Crisis but also the disruptions of the European Sovereign Debt Crisis. The similarity between net-percentage changes in credit standards, Fig. (2.3), and the MRP underlines the statement of Adrian, Moench and Shin [2] that this premium can be interpreted as a *market-based* view of the ease of banks' credit conditions.
As mentioned in the introduction, we want to relate the credit standard adjustments to the market-based assessment of macroeconomic risk. This is what we do in the next section.

2.4 Relative Risk-Taking

Our understanding of risk-taking does not only reflect pure changes in credit standards, as most of the related literature does, but moreover evaluates them with the prevailing and expected economic conditions. This results in a judgment of the appropriateness of credit standard changes. If they react stronger than the overall macroeconomic risk indicator, this can be a sign of excessive risk-taking, as banks adjust their credit standards more than appropriately, compared to the market-based financial substitutes, for a given macroeconomic risk inherent in Europe. Thus, we relate both variables shown and derived in previous sections in one variable. The basic idea is the following:

$$excessiveness = \frac{credit\ standard\ adjustments}{prevailing\ macro\ risk}.$$

Due to their measurement or construction, respectively, they cannot be directly related in one fraction. When looking at the ordinate axis of the MRP, Fig. (2.4) and net percentage credit standard changes (NPC), Fig. (2.3), we see that their values are hardly comparable. Credit standard adjustments are extracted from an ordinarily scaled, query-based variable and the resulting net-percentage changes are measured in a specific type of bounded cardinal scale, while the MRP is purely cardinal and (theoretically) not restricted to a predetermined range. As depicted in Eq. (2.6), we overcome this problem by standardizing both variables to make their movement more comparable and therefore relatable.

$$RRTM_{i;t} = \frac{(NPC_{i;t} - \overline{NPC_i})\sigma_{CS_i}^{-1}}{(MRP_t - \overline{MRP})\sigma_{MRP}^{-1}} \tag{2.6}$$

One problem associated with this approach is the sensitivity of mean and standard deviation to the observed period, but, as mentioned earlier, the availability of survey data limits our sample to start in 2003. This approach, depicted in Eq. (2.6), results in four different Relative Risk-Taking Measures (RRTMs, hereinafter), each reflecting a specific category of private sector lending. This variable fluctuates around zero and is driven by slight discrepancies in the movement of the very similar variables credit standard changes and macroeconomic risk.

Changes in each $RRTM$ can result either from dominating movements in the numerator or the denominator. If our $RRTM$ increases, $\Delta RRTM > 0$, disproportionately increases in credit standards or disproportionately decreases in macroeconomic risk can be a cause for this movement. Of course, the opposite holds for decreases in our measure. In the presence of, for instance, expansionary monetary policy, we expect that both variables involved in the construction of our $RRTM$ decrease. The variable that reacts relatively stronger will drive the overall direction. In the next section, we will include these measures in various VAR models.

2.5 Vectorautoregressions

We use quarterly log-differentiated, seasonally adjusted data in a five-variable reduced-form VAR model[14]:

$$Y_t = A_p(L)Y_{t-p} + c + \varepsilon_t \tag{2.7}$$

Y_t in Eq. (2.7) contains GDP-growth, Harmonized Consumer Price Index inflation, a short-rate, the respective four different $RRTMs$, and the credit-growth of the respective category. $A_p(L)$ is a lag polynomial coefficient matrix of order p[15], c is a constant vector and ε_t is the column vector of white noise error terms with covariance matrix Σ_ε. We use a shadow short-rate provided by Krippner [13] to account for the effects of unconventional measures undertaken by the ECB after policy rates hit the zero-lower-bound in 2013.

Within this paper, we focus on two distinct samples: the first starts in Q1 2003 due to the availability of BLS data and ends in Q3 2018 (full sample, FS, hereinafter), the second begins in Q1 2008 and ends in Q3 2018. This distinction is motivated by the introduction of a wide set of unconventional monetary policy measures as a reaction to the Financial Crisis (FC sample, hereinafter).

To conduct a structural analysis which accounts for the contemporaneous interdependencies of the implied underlying structural VAR model of the form

$$B_0 Y_t = B_p(L)Y_{t-p} + D + u_t, \tag{2.8}$$

identifying restrictions are needed to separate orthogonal, structural error terms from the covariance matrix Σ_ε. We use two identification approaches: sign restrictions, motivated by common theoretical and empirical wisdom, and cholesky decomposition with its implied recursive ordering for robustness.

Sign Restrictions

Identifying a VAR model with sign restrictions needs specific, plausible relations between the structural innovation of interest, here the monetary policy shock, and the other model variables. Uhlig [27] provides a detailed overview of the underlying ideas and procedures that we use.

In this paper, we only focus on the identification of monetary policy shocks as we are primarily interested in the effects of monetary policy on risk-taking and credit-

[14]One point necessary to mention is that, in general, the reduced-form VAR models in log-levels face stationary problems, e.g. in most cases the coefficient matrix $\hat{A}_p$ has at least one absolute eigenvalue greater than one. Thus, we estimate the VAR model in growth rates.

[15]The lag length is set to two for all presented models because it was the most frequent outcome in the different model setups when using common lag-length criteria.

granting behavior of euro area banks. Other structural innovations to the model are ignored further on.
Tab. (2.3) shows the imposed restriction scheme on the reaction of model variables to an expansionary monetary policy shock:

Variable	GDP-growth	HICP-inflation	short-rate	RRTM	Credit-growth
Restriction	+	+	-	none	none

Table 2.3: Sign restrictions for an expansionary monetary policy shock.
Notes: The assumed restrictions last for two quarters but the results are not very sensitive to the imposed duration.

The underlying assumptions of this identification scheme are quite common, theoretically plausible and empirically confirmed. Expansionary monetary policy does not dampen output and inflation via lower interest rates. To get an unfiltered perspective of the underlying data, the variables of major interest, $RRTM$ and credit-granting, are kept unrestricted[16]. In the following, we briefly discuss the procedure that yields the structural representation of our model and the impulse response functions linked to it.
Within our estimation, we randomly draw from a Whishard distribution, that is characterized by the reduced-form covariance matrix of our VAR model in Eq. (2.7). We do so until we reach 5,000 draws that satisfy the conditions depicted in Tab. (2.3). The respective rate of acceptance that reflects the share of accepted draws over the total amount of randomly generated multivariate candidate matrices, varies between 12% (FC, housing) and 14 % (FS, housing), depending on the sample and category under consideration. From the set of 5,000 suiting draws, that yield 5,000 different propagation paths of structural innovations in the short-rate, we exclude those that are above the 84^{th} and below the 16^{th} percentile.

2.6 Results

The presentation of our impulse response functions is split into two parts that differ by the sample under consideration. As mentioned before, we focus on the effects of monetary policy shocks only, for a horizon up to 20 quarters, i.e. five years. Because the reactions of macroeconomic variables output, prices, and interest rates are per construction in line with the well-confirmed reaction patterns, they are not discussed

[16]Imposing a reaction on credit growth via the implications of, for instance, the credit channel might be an option for periods of well working monetary transmission. We keep it unrestricted to account for possible distortions during the recent financial crisis, see ECB [9].

hereinafter. Nevertheless, they are available on request. As our $RRTMs$ stem from two standardized variables, collected in one fraction, they are very sensitive to, for instance, opposing signs in numerator and denominator, or to small differences in the direction of the included variables. For the sake of illustration, the ease of interpretation, and to emphasize the disproportionality that drives the reaction of our measure, Fig. (2.13) in the appendix shows impulse response functions of non-financial private sector credit standards and credit growth to expansionary monetary policy shock.[17] As a side effect, this provides additional evidence for the existence of the risk-taking channel and the dominating role of credit standard adjustments in it, i.e. the perspective most literature has on this channel. Additionally, we can see that the lowering of credit standard is slightly larger in the sample that starts in 2008. All monetary policy shocks discussed in this paper are 25bp interest rate cuts.

2.6.1 Full sample

Fig. (2.5) shows response functions of our four $RRTMs$. As we can see, the median response is in all four cases negative. A negative reaction of the $RRTM$ can be a result of a more than proportional lowering of the numerator, the credit standards, or can be rooted in a more than proportional increase in the denominator, macroeconomic risk. The first scenario is indicated in Fig. (2.13), appendix, the last one is counter-intuitive and unlikely. Expansionary monetary policy cannot be expected to increase macroeconomic risk, at least not in the short- and medium-term, which we consider. Impulse response analysis to back up this claim is available upon request.
Fig. (2.5, a) shows the response of the overall non-financial private sector. Credit standards seem to loosen stronger than the overall macroeconomic risk variable extracted from loans' substitutes, which indicates excessive risk-taking by financial intermediaries in periods of expansionary monetary policy, significant after six quarters. The most pronounced reaction when looking at the three subcategories can be observed for non-financial corporations' credit standards, Fig.(2.5, c), while credit standards for house purchase, Fig. (2.5, b), do almost not react significantly, overall. Surprisingly, consumer credit standards show a significantly positive reaction between three and five quarters after the shock, then turning negative, too.
When taking a look at the quantitative perspective, granting credit, Fig.(2.6), non-financial sector credit growth shows the expected positive sign, but with a lack of significance for the here presented percentiles. This finding alike holds for all subcategories.

[17]All other categories are available on request.

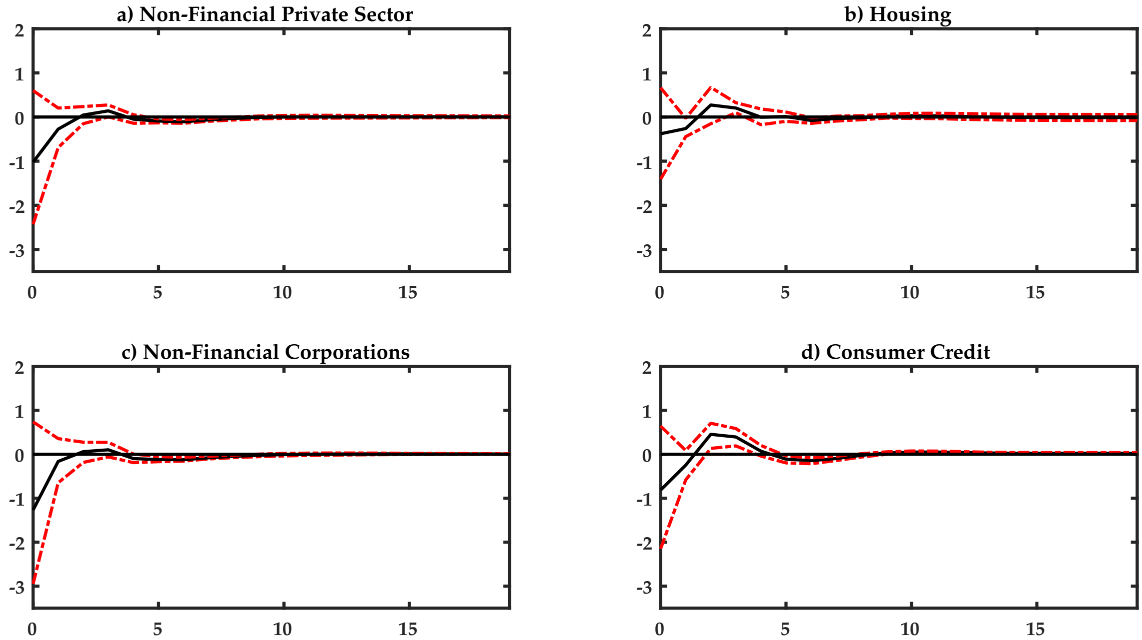

Figure 2.5: Impact of a 25 bp expansionary monetary policy shock on the RRTM of the respective category, full sample.
Notes: The solid black lines reflect the median response, the dotted red lines are the 16^{th} and 84^{th} percentiles.

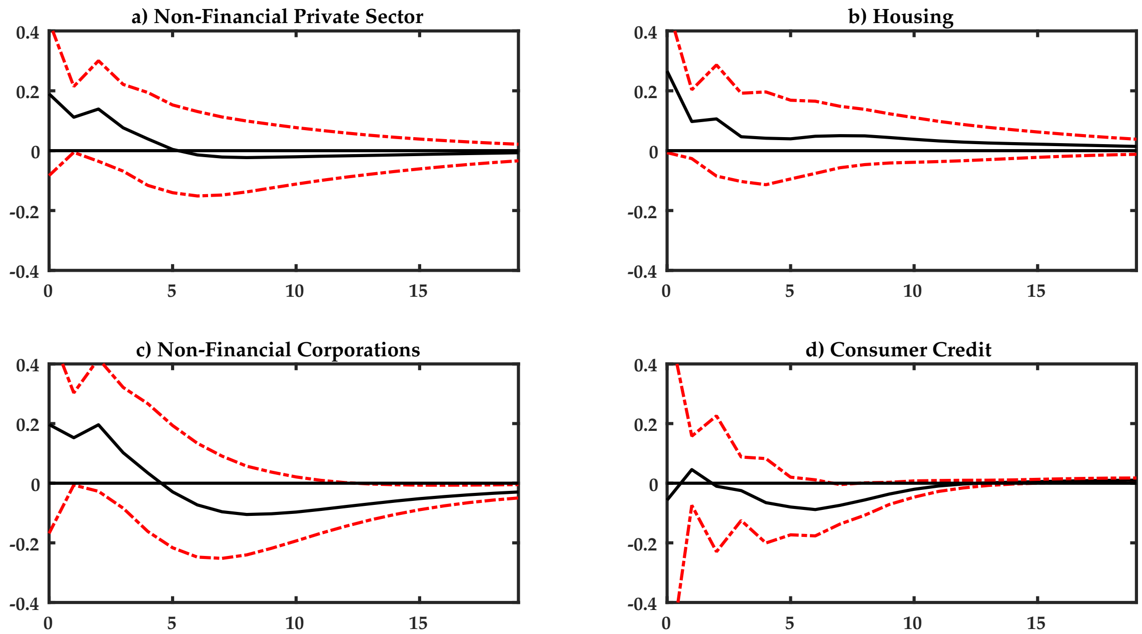

Figure 2.6: Impact of a 25 bp expansionary monetary policy shock on the credit growth of the respective category, full sample.
Notes: The solid black lines reflect the median response, the dotted red lines are the 16^{th} and 84^{th} percentiles.

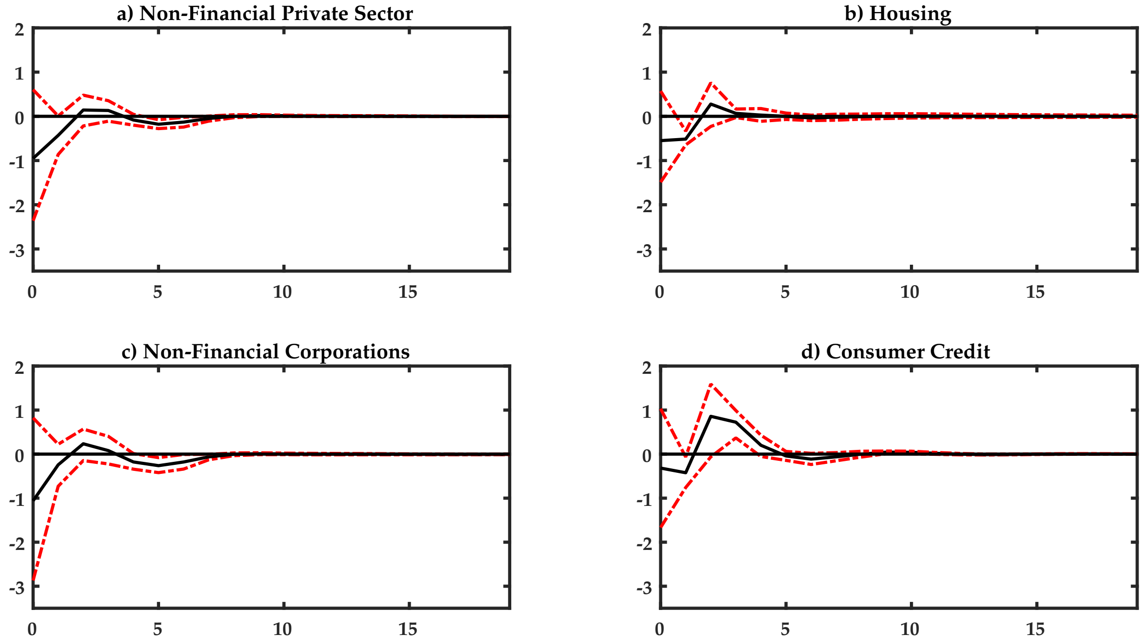

Figure 2.7: Impact of a 25 bp expansionary monetary policy shock on the RRTM of the respective category, FC sample.
Notes: The solid black lines reflect the median response, the dotted red lines are the 16^{th} and 84^{th} percentiles.

2.6.2 Financial Crisis Sample

Changing the sample such that it starts in Q1 2008, the reactions of our key variables, $RRTM$ and credit growth, indicate slight differences compared to our full sample model. Fig. (2.7) displays the results. Decreases in the $RRTMs$ are stronger and more persistent for the categories of major relevance: corporate loans and mortgages. For mortgage credit standards, Fig. (2.7, b), we can observe a short, but significant reaction already after two quarters. Again, in the business area of consumer credit, we cannot observe this disproportional lowering of standards, our variable even increases significantly between two and four quarters after the shock. This indicates that the amplifying nature of the risk-taking channel is more pronounced in periods of extraordinary expansionary (unconventional) monetary policy for mortgages and, to a lesser extent, for non-financial corporations' loans.

Fig. (2.8) shows the responses of credit growth to a monetary policy shock. The overall non-financial private sector, Fig. (2.8, a) shows the expected positive reaction, which remains significant for three quarters. This finding is primarily driven by the growth in mortgages, see Fig. (2.8, b), while credit growth in the non-financial corporation sector shows a positive, but non-significant reaction[18]. Consumer credit

[18] Recall that one motivation for some unconventional monetary policy measures in the euro area

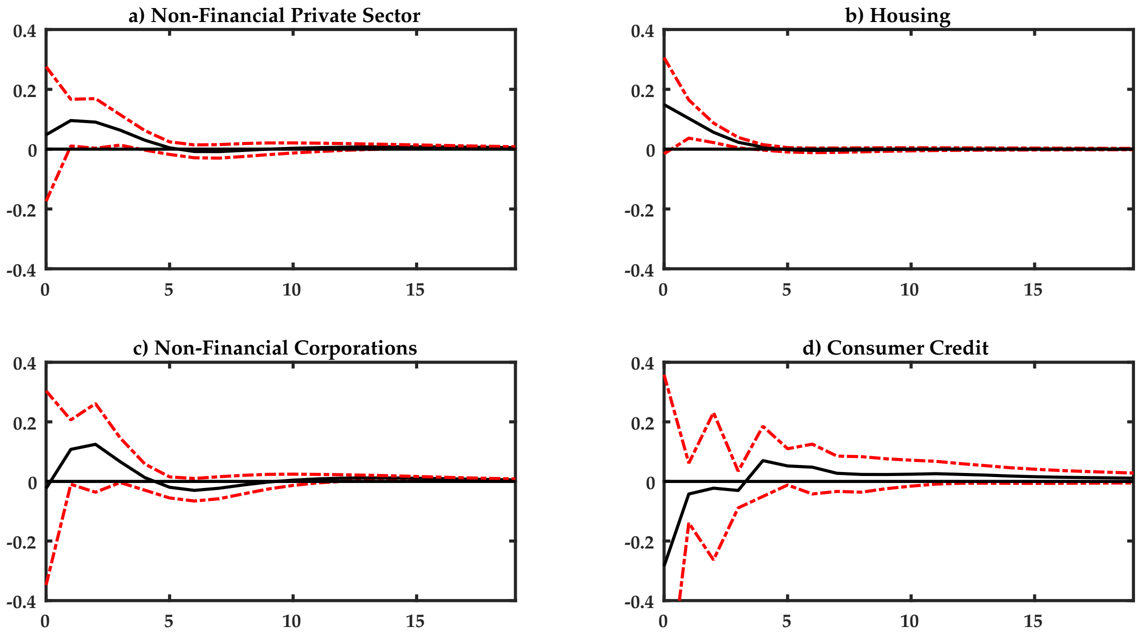

Figure 2.8: Impact of a 25 bp expansionary monetary policy shock on the credit growth of the respective category, FC sample.
Notes: The solid black lines reflect the median response, the dotted red lines are the 16^{th} and 84^{th} percentiles.

growth, Fig. (2.8, d) shows, similar to the full sample model, no significant reaction. Besides the similar and more persistent reaction in relative risk-taking, the reaction related to real estate financing is most noteworthy from the credit growth perspective and notably different from the reaction in the model that deals with the corporate sector discussed before. In Fig. (2.8, b) we see that the amount of granted credit to finance housing reacts most intense, compared to the residual categories and thus seems to drive the reaction in overall non-financial sector credit growth, as discussed before. This indicates that, in contrast to lending to firms, mortgage growth is more affected by monetary policy shocks. These findings are in line with the Ausschuss für Finanzstabilität [5] who emphasize that in the euro areas' biggest economy, Germany, primarily the real estate sector investments expanded during the recent extraordinary long low-yield environment. Interestingly, and in contrast to the results of other credit categories, the smallest category, credit standards for consumers, do not react in a risk-taking-indicating manner in both sub-samples, but due to the low share of this category on overall credit granting, see Fig. (2.1), this finding does not have a sizable effect on the findings for the overall non-financial private sector.

was to restore credit provision to the non-financial private sector, especially to non-financial corporations.

Summing up, we find indeed disproportionality in the adjustment of credit standards, while credit growth often shows the expected positive sign, but lacks significance.

2.7 Robustness

Cholesky Identification

As outlined by Sims [20] and in contrast to the sign restriction approach, cholesky-based identification utilizes the recursive order of variables in Y_t to restrict contemporaneous interactions of the reduced form VAR model. GDP and prices react slower due to, for instance, nominal rigidities, implying that they are ordered first. Central banks adjust their monetary policy periodically to recent developments in macroeconomic key variables, GDP-growth and HICP-inflation, thus the monetary policy variable is ordered behind them. Fast reacting financial variables are impacted by macroeconomic as well as by short-rate changes. This results in the following order which is standard in macroeconomic VAR literature:

$$Y_t = [GDP_t \quad HICP_t \quad \text{short-rate}_t \quad RRTM_{i;t} \quad Credit_{i;t}]' \tag{2.9}$$

Fig. (2.9) shows the impulse response functions for the set of VAR models described in Sec. (3), now identified via an assumed underlying temporal relationship regarding reaction inertia, reflected in Eq. (2.9).

Although the variables of major interest, $RRTM$ and credit growth, show less significant reactions to a monetary policy shock, the mean responses indicate the same underlying mechanisms. All four categories[19] analyzed in this paper show the same behavior in the $RRTM$ and also the corresponding credit growth variable does not react significantly. Thus, the results presented in the previous section are, to a weaker extent, confirmed. Expansionary monetary policy shocks seem to lead to disproportionately strong decreases in credit standards, while the credit growth variable is, in general, not affected the way we would have expected it to be during this sub-sample.

2.8 Conclusion and Outlook

The assessment of risk-taking by euro area banks remains a challenging issue. After a short overview of banking in the euro area that emphasizes the lowering effect of

[19] Although we present for the sake of clarity only results for the non-financial private sector, the complete set of impulse response functions of the robustness section is available on request.

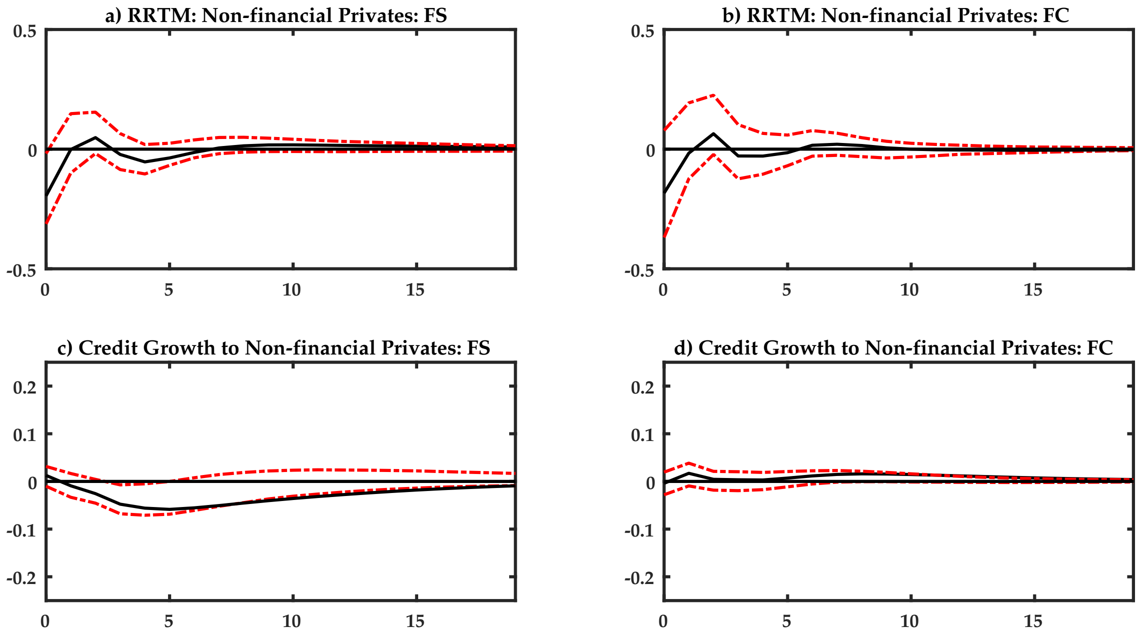

Figure 2.9: Impact of a 25 bp expansionary monetary policy shock on credit standards and credit growth: non-financial private sector, cholesky identification.
Notes: The solid black lines reflect the mean response, the dotted red lines are +/- one std. dev. confidence bands.

periods of unconventional monetary policy on credit standards, we suggest a new measure to evaluate changes in credit standards with an estimated macroeconomic risk measure. This variable captures the risk prevailing in the economy via bond market information. Bond markets are suitable for this purpose because they contain various information about current and expected economic performance and they are close substitutes to loans. Thus, the co-movement between system inherent macro-risk and changes in credit standards can be used to assess *excessive risk-taking* in the financial sector. This can help to better unveil the role banks play as a financial accelerator within the transmission of monetary policy via the risk-taking channel. The suggested measure might help to uncover unintended developments, i.e. inappropriate granting of credit, in the financial system that is induced by unexpectedly loose monetary policy.
Although the assessment of risk-taking remains hard, our suggested Relative Risk-Taking Measure shows that credit standards fluctuate on average *more than proportionately*, relative to the overall risk when confronted with expansionary monetary policy shocks. These findings can be testified for three out of the four categories dealt in this paper. Reactions of credit growth indicate distortions in monetary policy transmission. The results remain in principle similar if our VAR model is

identified via cholesky and its implied ordering, albeit their significance decrease. When focusing on the recent financial crisis, the magnitude of these findings in our Relative Risk-Taking Measure increases slightly. This indicates probably the problematic aspect of long-lasting low-yield periods, which characterize this sample. Credit growth in the non-financial private sector is primarily driven by growth in housing finance, while credit-granting to non-financial corporations shows an either insignificant or even opposing reaction. The implications of these outcomes are probably problematic. Within long-lasting periods of low interest rates, accommodative monetary policy might cause credit standards to adjust in a way that bears the risk of vulnerable bank balances in the long-term, as they acquire new and riskier assets: loans to less credit-worthy borrowers. This caveat might occur especially in the real estate sector and, in turn, might cause systemic imbalances in the overall financial system and thwart monetary policy intentions of calming and stabilizing financial markets in the long run.

Some interesting points for further research are e.g. alternative modeling setups to clearer elaborate differences between distinct periods. Furthermore, a detailed look at the different categories queried in the Bank Lending Survey might unveil new insights about monetary policy effects in dependence of firm size or credit duration. Also, a more precise differentiation among the various kinds of unconventional monetary policy measures and announcements to achieve a clearer distinction between e.g. balance sheet policy and forward guidance could shed light on the effects of the ECB's unconventional monetary policy and its conduction on banks' risk-taking activities. Last, and probably most promising, would be a country-specific perspective, as the BLS also contains country-specific data of e.g. credit standard adjustments.

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2.9 Appendix

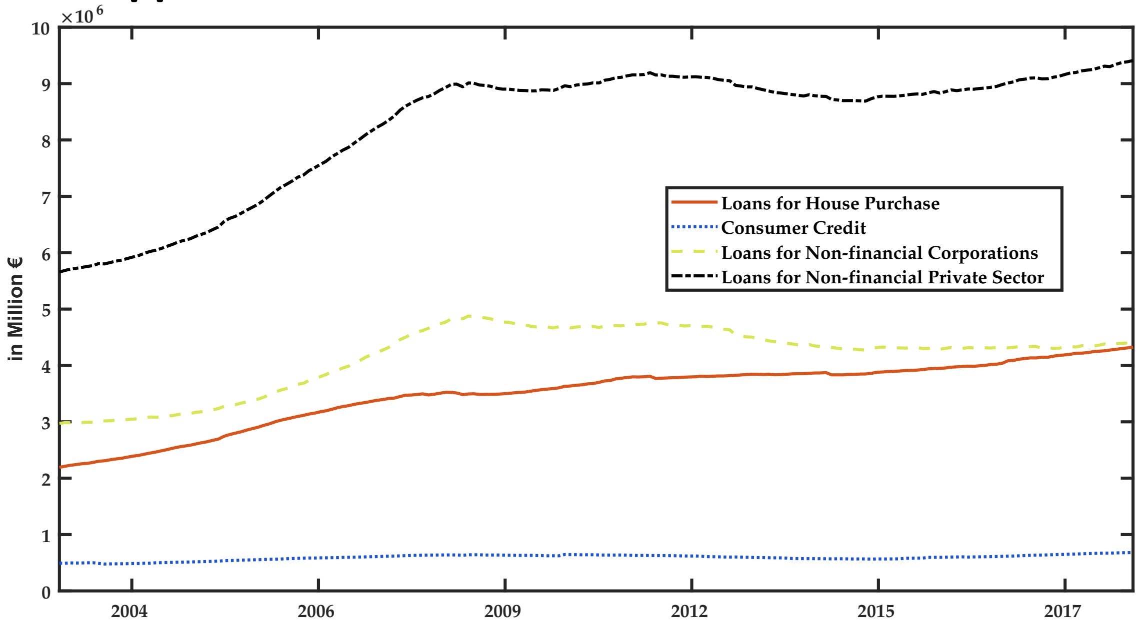

Figure 2.10: Stock of outstanding loans of the three in the BLS queried non-financial private sector credit categories.
Notes: Non-financial corporation loans (yellow-dashed), Mortgages (red-solid), consumer credits (blue-dotted), and sum of all (black dashed-dotted).
Source: ECB Statistical Data Warehouse, author's calculations.

8. Please indicate how you expect your bank's credit standards as applied to the approval of loans or credit lines to enterprises to change over the next three months. Please note that we are asking about the change in credit standards, rather than about their level.

	Overall	Loans to small and medium-sized enterprises	Loans to large enterprises	Short-term loans	Long-term loans
Tighten considerably					
Tighten somewhat					
Remain basically unchanged					
Ease somewhat					
Ease considerably					

21. Please indicate how you expect your bank's credit standards as applied to the approval of loans to households to change over the next three months. Please note that we are asking about the change in credit standards, rather than about their level.

	Loans for house purchase	Consumer credit and other lending
Tighten considerably		
Tighten somewhat		
Remain basically unchanged		
Ease somewhat		
Ease considerably		

Figure 2.11: Bank Lending Survey, questionnaire to expected credit standard changes that are used within this paper.
Source: ECB BLS The questionnaire, revised version, introduced in April, 2018.

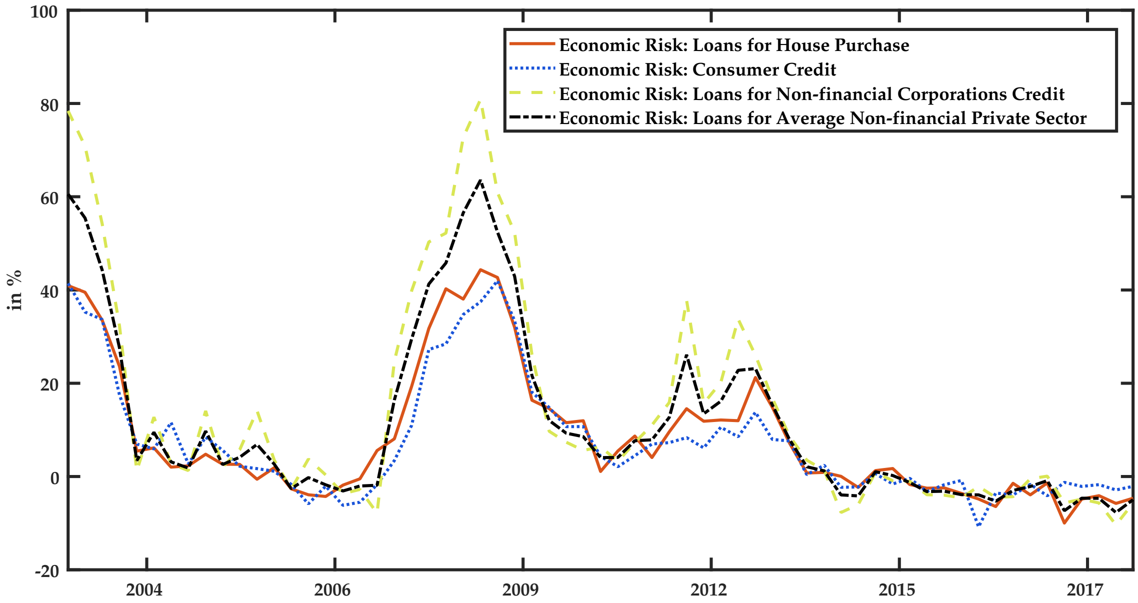

Figure 2.12: BLS: Net effect of economic risk on private sector credit.
Notes: Housing Credit (red-solid), Consumer Credit (blue-dotted), Non-financial Corporations (yellow-dashed), and Non-financial Private Sector (black-dashed).
Source: ECB Statistical Data Warehouse, author's calculations.

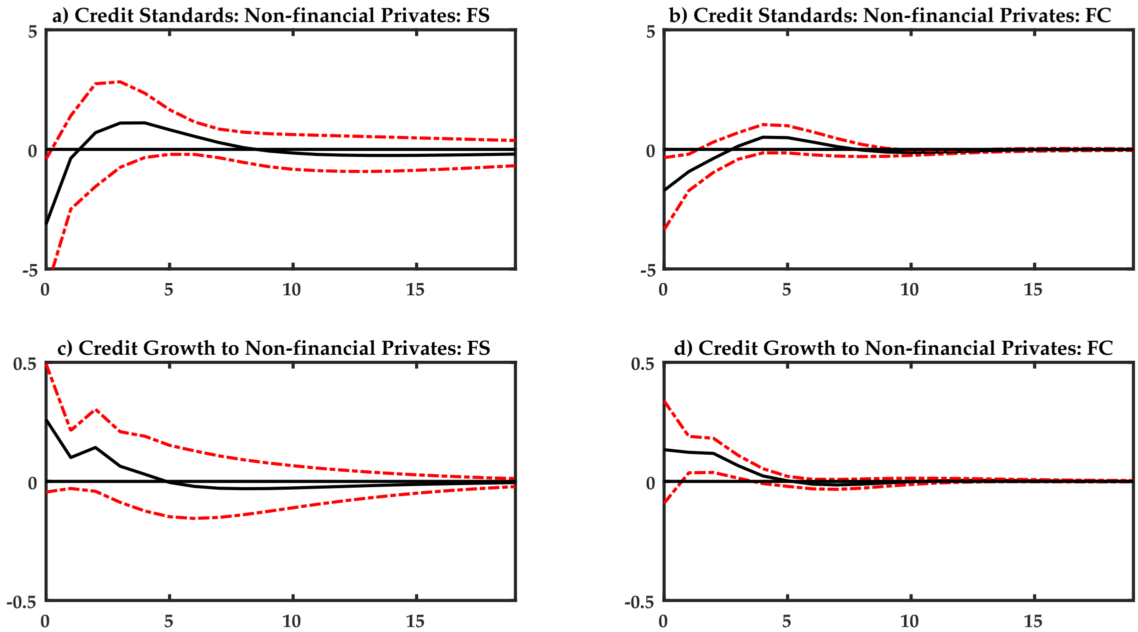

Figure 2.13: Impact of a 25 bp expansionary monetary policy shock on credit standards and credit growth: non-financial private sector. Identification obtained via sign restrictions, with the same restrictions as in Tab. (2.3), except that credit standards replace RRTM.
Notes: The solid black lines reflect the median response, the dotted red lines are the 16^{th} and 84^{th} percentiles.
a) and c) stem from the model of the full sample, b) and d) from the Financial Crisis sample.

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

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II. International Network for Economic Research (INFER): 22nd Annual Conference, 06/2020, postponed to 12/2020, Paris, France.

III. 4th Workshop on Financial Econometrics and Empirical Modeling of Financial Markets: 05/2020, postponed to 09/2020, Chemnitz, Germany.

IV. Royal Economic Society (RES) Symposium of Junior Researchers 2020: 04/2020, canceled, Belfast, United Kingdom.

V. Gießener Graduierendenzentrum (GGS):
Section Behavioral and Social Finance & Accounting:
Doctoral Lunch, 06/2019, Gießen, Germany.

VI. VWL V Brown Bag Seminar Series:
05/2019, Gießen, Germany.

VII. MAGKS Doctoral Colloquium:
Annual Meeting, 03/2019, Rauischholzhausen, Germany.

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

Jörg Schmidt*,[1]

This paper investigates in how far monetary policy shocks impact European asset markets, conditional on different risk states. We distinguish between macroeconomic risk, political risk, and financial risk and 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-vectorautoregressive model that contains assets and a short-rate. 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 low 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 low. 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. Interestingly, financial equity reacts positively or insignificant to hikes in short-rates. The positive reaction is most pronounced for states of high financial risk. Consequently, monetary policy transmission via distinct asset markets highly depends on the degree of these different kinds of risk inherent in European asset markets.

Keywords: state-dependency, asset pricing, monetary policy

JEL classification: C11, E44, G12

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3.1 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 the 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.

However, given that the term risk is not a narrow one, answering these questions is not straight forward. Aggravating, there exits much overlapping to uncertainty, see e.g. Bekaert et al. [10]. 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 by Hansen [25]. Systematic risk cannot be eliminated via additional diversification, thus it requires compensation for bearing it, for instance, a risk premium. It is a phenomenon subject to all assets, but to a varying degree, see, e.g., Inkinen et al. [27]. On the contrary, systemic risk is a vague concept that, especially nowadays, 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 the risk that stems from different aspects of European financial markets.

Within this paper, we want to examine the existence of asymmetric reactions of various asset prices to an unexpected change in short-rates, conditional on distinct regimes of different risks inherent in Europe. Does their reaction show state-dependency? And what implications result from potential asymmetries for monetary

[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.

policy makers when we are in different risk regimes? 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?

To answer these questions, we proceed as follows. First, we recapitulate the role risk plays to determine the value of an asset. We then quantify the degree of three types of risk that are subject to all assets we deal within this paper: macroeconomic, (economic) policy, and financial risk. We extract these risks from a set of variables via principal component analysis (PCA). Next, we study different risk regimes that arose in the euro area, respectively. The resulting distinction between high- and low-risk regimes fits into the literature about state-dependent effects of monetary policy. We then analyze within vectorautoregressions the sensitivity of equity and corporate bond yields to monetary policy shocks, conditional on high or low risk inherent in European markets, respectively.

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 low 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, they show a strong state-dependency if we distinguish between periods of high or low political risk while non-investment-grade bonds display only a minor difference across high or low political risk states. For equity, we find diverging results, depending on the respective sector: equity of industrial firms shows, depending on the model, less intense reactions to monetary policy shocks in regimes of low macroeconomic or high political risk while equity of European banks is, surprisingly, positively affected by monetary policy shocks when financial risk is elevated.

This paper fits into several strands of the existing literature. The general idea to augment a vector-autoregressive (VAR) model with factors is prominently promoted by e.g. Bernanke et al. [11]. 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 a monetary policy tightening has on macroeconomic variables. Furthermore, we follow Alessandri and Mumtaz [4]

and make use of state-dependent sensitivity of variables to monetary policy shocks. They investigate within a threshold-VAR (TVAR) model, in how far the reaction of macroeconomic series is state-dependent, conditional on high or low financial risk, respectively. Tenreyro and Thwaites [37] 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 future economic policy, decreases real activity, as outlined in Fernández-Villaverde et al. [20]. This finding is even more pronounced during periods characterized by very low interest rates.
Unveiling time-variation in risk premia of US equity is the aim of Gagliardini et al. [21]. 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 extent from their standard, time-invariant, counterparts during crises periods. This emphasizes the need to account for possible regime-dependent non-linearities.

Regressing risk-related measures on financial variables or evaluating the impact of unexpected changes within VAR models is a common practice to quantify the tense relationship between asset prices, monetary policy, and risk. Beirne [9] shows in how far the Euro OverNight Index Average (EONIA) is driven by liquidity needs and credit factors, both in normal times and during periods characterized by unconventional monetary policy with its altered allotment procedures that accompany it. Aastveit et al. [1] quantify the effects of monetary policy shocks on the US economy, conditional on high or low uncertainty. They differentiate between three uncertainty classes: macroeconomic uncertainty, measured by the macroeconomic uncertainty factor of Jurado et al. [29], economic policy uncertainty, using the EPU index of Baker et al. [8], and (implied) financial market volatility. An important finding for this paper is that the transmission of short-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 [28] or Chen [16]. 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 papers find that monetary policy has a larger impact on assets when they are in bear markets.

[2]While testing for robustness, the authors also show that their findings hold in an environment characterized by the zero-lower-bound (ZLB) and that the usage of shadow-short-rates is appropriate.

Many papers have in common that they narrowly focus on one specific type of risk or state, neglecting possible interactions among different kinds of risk. We want to emphasize the distinction among these three types of risk in our paper, which the literature often picks up separately and selectively, or does not distinguish across these different dimensions of risk. We, instead, believe that they rather interact with each other and should not be treated as a solitary or unitary phenomenon. One prominent example is the European Government Debt Crisis, where all three types of risks were elevated, as we will see later on.
Furthermore, we want to focus on asset prices instead of real activity for two reasons: First, 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 risks and differences in pricing mechanisms. Thus, asset prices are possibly susceptible to adjustments in the monetary policy stance or unexpected changes in short-rates, as outlined by Benoît Cœré. Second, asset prices are an important element within monetary policy transmission mechanisms. The possible risk-state dependency of their sensitivity to monetary policy adjustments needs to be subject to investigation to better understand monetary policy transmission via asset prices and their respective markets.

3.2 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 a focus on industrial firms, EUROSTOXX Industrials (ESIndustrials), and a bank equity index, EUROSTOXX Banks (ESBanks), both total return indices. We use total return indices to also account for paid dividends. Regarding yields, we focus on long-term corporate bonds from two rating classes. We use AA-rated corporate bonds with a ten-year maturity[3], and riskier corporate bonds summarized in a high-yield index[4] with maturities between seven to ten years.

The four series are in Fig. (3.1). 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

[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.

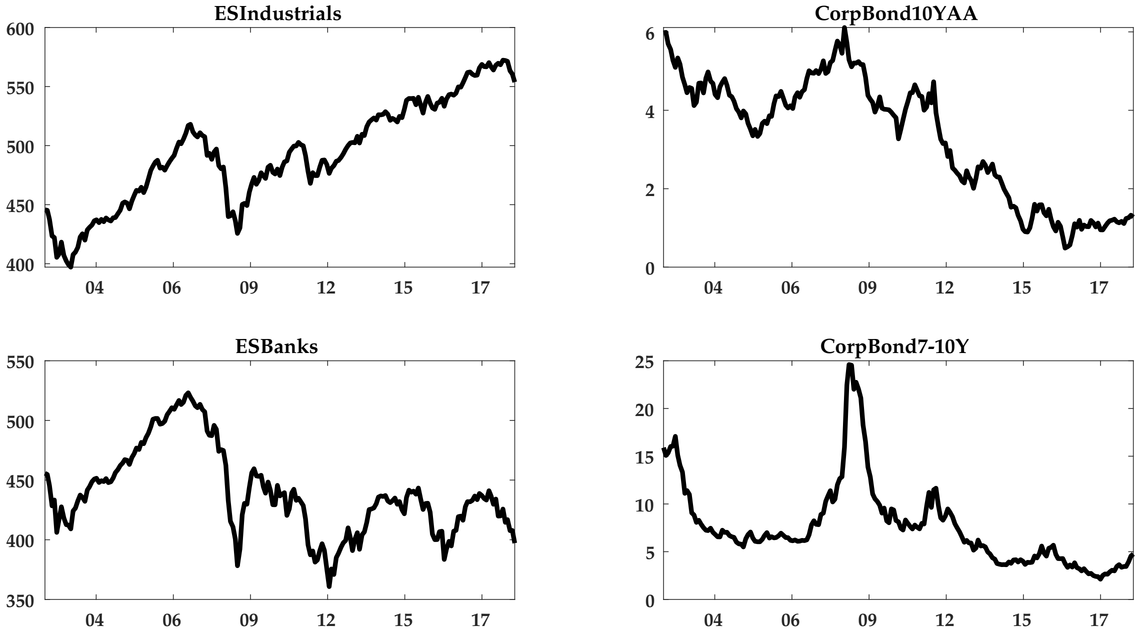


Figure 3.1: Euro area assets: EUROSTOXX indices for industrial firms and banks (left column, in ln*100) and yields of corporate bonds (right column, in percent).
Notes: Stock indices are total return indices, while bond yields are yields to maturity.

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 lowering of policy rates. Also here, we can see crises effects, as both series show hikes with different sizes during crises 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 lower bound of investment-grade bonds. Since we use euro area government bonds as a variable to extract political risk in Sect. (3.3), we do not include them in this paper as an asset of interest.

3.3 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. We especially focus on what role the perception of risk and short-rates play within these mechanisms, and how asset prices are expected to react to changes in these crucial determinants.

The value of an asset V_i at time t, e.g. a stocks or bonds, can be described as a function of expected future cash-flows (CF), discounted with expected future risk-adjusted discount rates $r_{i,t}$. Assuming efficient capital markets, asset prices should only follow a random walk, except new information enter the pricing mechanisms or the assessment of existing information changes. Eq. (3.1) reflects these considerations:

$$V_{i,t} = f(E\left[\sum_{t}^{d} \frac{CF_{i,t}}{(1+r_{i,t})^t}\right] + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma_{V_i,t}) \tag{3.1}$$

According to Cochrane [18], asset valuation is primarily dominated by the respective discount factors r_i that are linked to the riskiness of investments and expected short-rates. Following 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. (3.2):

$$E\big[r_{i,t}\big] \approx f(E\left[\frac{1}{d-t}\sum_{t}^{d} \mathrm{rfr}_t\right], \mathrm{tp}_{d,t}, \mathrm{rp}_{i,t}) + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma_{r_i,t}) \tag{3.2}$$

rfr_t refers to a consecutive risk-free investment over a horizon d, $\mathrm{tp}_{d,t}$ is a term premium that reflects real interest rate risk, and $\mathrm{rp}_{i,t}$ is a risk premia. For the same maturity, the demanded average rfr and tp 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 risks that are common to all assets, we call them common risks, (CRs), but to a varying extend ψ, 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 instance, bonds of sound firms should face a lower 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 k CRs, the relevance of a specific type of risk for the respective asset, $\psi_{j,t}$, and idiosyncratic risk, as outlined in Eq. (3.3)

$$\text{rp}_{i,t} = \sum_{j=1}^{k} \psi_{j,t} CR_{j,t} + IR_{i,t} + \epsilon_t \qquad \epsilon_t \sim N(0, \sigma_{rp_i,t}). \tag{3.3}$$

Following the elaborated mechanisms of this standard asset pricing nexus, we expect that increases or peaks in $CR_{j,t}$ affect asset prices as follows:

$$E\left[\frac{\partial(V_{i,t})}{\partial(CR_{j,t})}\right] \begin{cases} < 0, & \text{if } V_i \text{ is a stock index or a corporate bond.} \\ > 0, & \text{if } V_i \text{ is a bond yield.} \end{cases} \tag{3.4}$$

Eq. (3.4) states that increases in CR_j, or its perception, should lower stock prices or increase bond yields, in particular via its impact on discount rates $r_{i,t}$. The same considerations hold for changes in current or future expected short-rates, as stated in Eq. (3.5):

$$E\left[\frac{\partial(V_{i,t})}{\partial(\overline{rfr_t})}\right] \begin{cases} < 0, & \text{if } V_i \text{ is a stock index or a corporate bond.} \\ > 0, & \text{if } V_i \text{ is a bond yield.} \end{cases} \tag{3.5}$$

Increases in these rates should lower stock prices or increase bond yields through their impact on discount rates and CFs.

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 of 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. (3.2). This is the main motivation to use a VAR model that is described in more detail in Sect. (3.4). 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 low states of risk. This is where 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 in our VAR model. Within this paper, we differentiate between $k = 3$ types of CRs that all should have an impact on asset markets.[5] The three kinds of risk are depicted in Fig. (3.2).

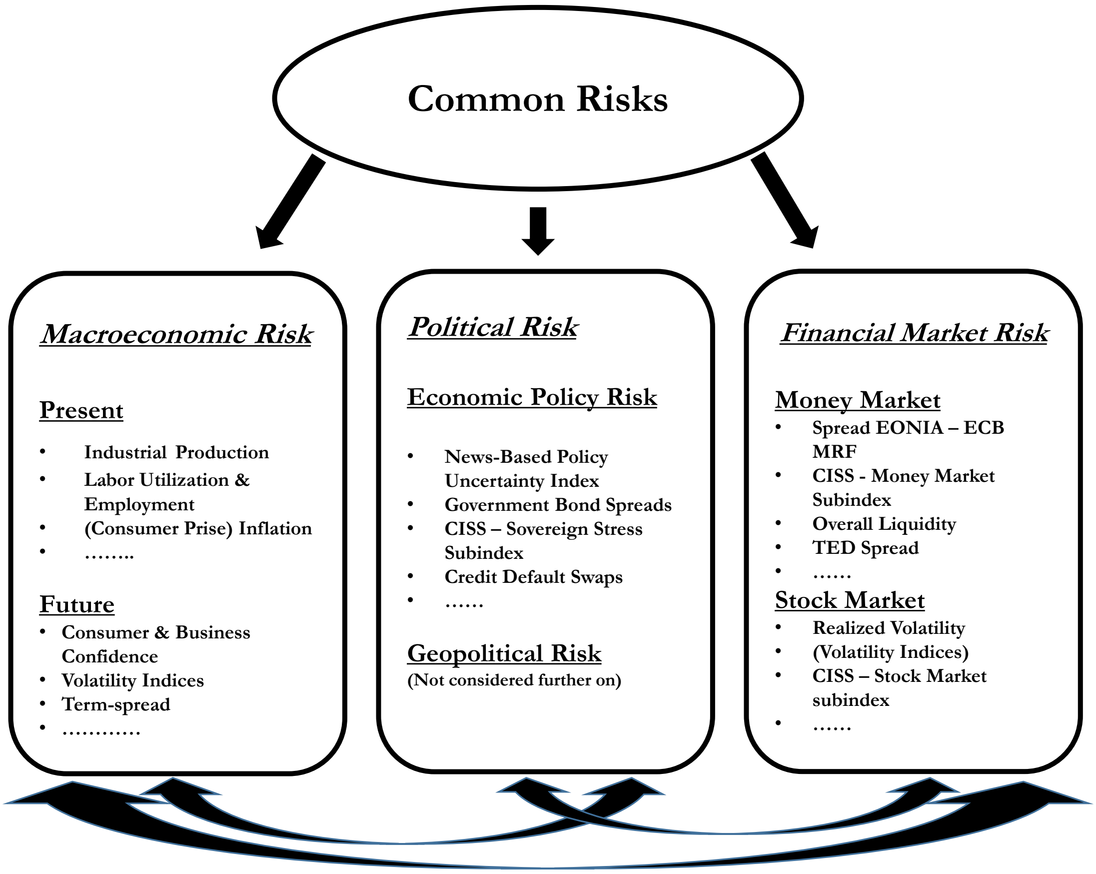


Figure 3.2: Common risks and their categorization, differentiation, and candidate variables for their measurement.

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. (3.5.1).

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

The risks 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 covariance matrix $\mathbf{X^T X}$:

$$(\mathbf{X}^T\mathbf{X})\mathbf{v} = \lambda\mathbf{v} \tag{3.6}$$

In Eq. (3.6), $\mathbf{v}$ equals the matrix of eigenvectors, in this context often referred to as loadings, and λ is a main-diagonal matrix 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 follows:

$$\mathbf{F_{t\times 1}} = \mathbf{X_{t\times n}v_{n\times 1}} \tag{3.7}$$

This approach is generally used by central bankers, researches and practitioners around the world. For example, Brave and Butters [14] use 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. We do so because the three assumed risk factors face a high degree of correlation during 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 allow 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. An alternative to this procedure is suggested by Koop and Korobilis [31]. They use a dynamic setup to address these concerns, using a time-varying-parameter factor-augmented VAR model. In particular, they select suitable variables to construct their FCI using macroeconomic and financial variables and let the contribution of these variables, expressed as time-varying coefficients and loadings, respectively, vary over time. The resulting factor enters in the next step a VAR model that consists of macroeconomic key variables, like prices and real activ-

ity. So they also emphasize the time-varying interaction between financial conditions and the macroeconomic environment. However, given that we want to distinguish between different risks, in particular more than two, in a categorical way, this approach does not fit to this paper. We do not want to estimate a financial condition index by using macroeconomic variables, as these macroeconomic variables enter our model separately later on, via the macroeconomic risk factor, together with political risk.One point worth to mention is that they estimate many different FCIs by setting the contribution of distinct financial variables to zero[6], which results in the meaninglessness of these variables for the estimation and average over the estimated FCIs. Thus, the assignment of the respective variables to a specific category remains hard and also ambiguous. For instance, the literature uses volatility indices in a blurry way. Haddow et al. [24] assign them to the longer-run, macroeconomic sphere (using an index for $\geq$ 12 months-ahead) while Andersen et al. [6] use them to capture short-run financial risk (index horizon $\leq$ 3 months-ahead). Thus, the horizon of these indices plays a role, too.

In the following, we will present candidate variables that are assumed to be primarily driven by a certain type of risk. Next, we capture the first principal component to which we refer in the following as risk factor $\mathbf{F_t}$. These ideas are depicted in Eq. (3.6) and Eq. (3.7). We show and discuss these factors for each type of risk depicted in Fig. (3.2), but also display the unexplained variation in the underlying variables, ϵ_t in Eq. (3.8), which is not explained by this one 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

$$\epsilon_{\mathbf{t}\times\mathbf{n}} = \mathbf{X}_{\mathbf{t}\times\mathbf{n}} - \mathbf{F}_{\mathbf{t}\times\mathbf{1}}(\mathbf{v}_{\mathbf{n}\times\mathbf{1}})^T, \tag{3.8}$$

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. (3.8) to Tab. (3.10), appendix. As can be seen, the first component captures in all three different categories of risk the absolute majority of variation in the respective data series.

[6]They do so by restricting the loadings of the respective variables to zero.

3.3.1 Macroeconomic Risk

We interpret macroeconomic risk as the risk that stems from business cycles. Hence, we select variables similar to Stock and Watson [36] 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, a real-time economic activity measure provided by CEPR, and new orders as well as capacity utilization of the industry.

The sentiment and confidence about the near future and the then prevailing macroeconomic conditions are 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. It has high predictive power for future macroeconomic performance and thus is often acknowledged as a leading indicator for recessions, see e.g. Estrella and Hardouvelis [19]. The VDAX, a 12 month-ahead implied volatility index for the German DAX[7], 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 month-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. (3.5), appendix. Moreover, Fig. (3.3) shows the resulting estimate for our macroeconomic risk factor and the respective residuals for each variable we use.

3.3.2 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 (CDS). As their data is reliable and easy to obtain, they are wide-spread measures of economic-policy risk. Aizenman et al. [2], for instance, regress euro area and non-euro-area CDS on a set of fiscal variables. A key

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

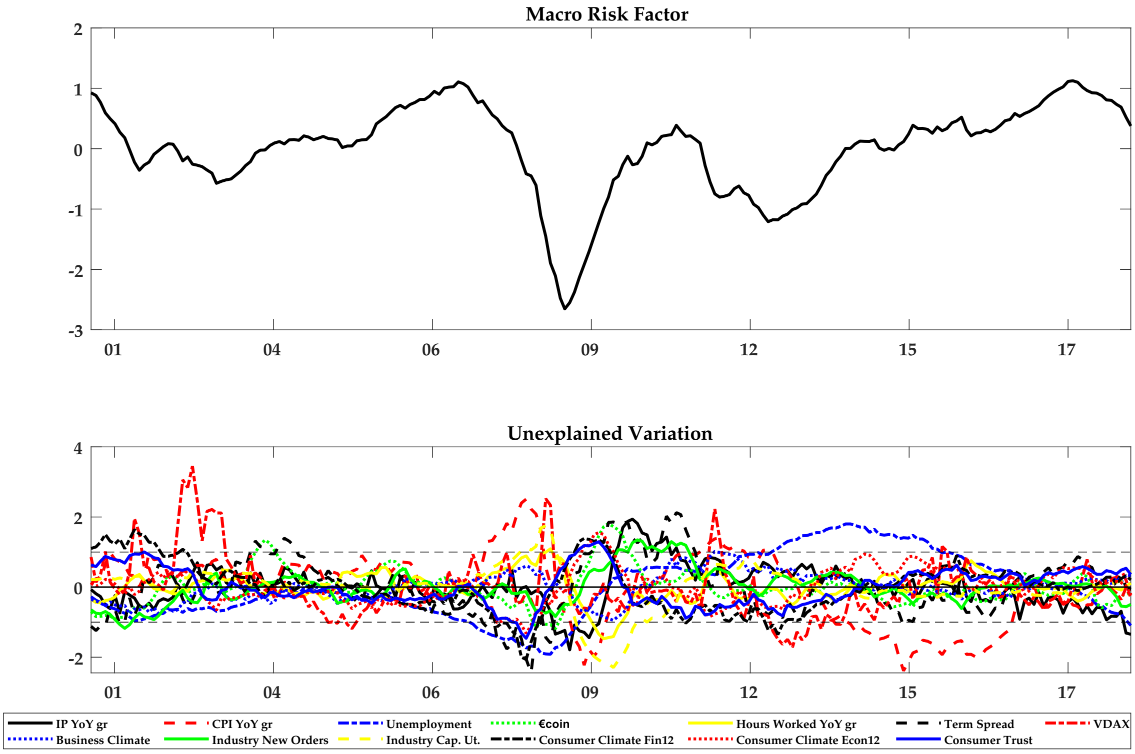


Figure 3.3: First principal component, referred to as Macro Risk Factor (MRF), of variables in Tab. (3.5) (upper picture) and residuals $\epsilon_{t \times n}$ of variable movement that is not explained by the common component (lower picture).

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. [12] 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, but also liquidity within the respective bond markets. Summarizing, CDS and yield spreads reflect are appropriate measures to assess fiscal and economic-policy risks.
The second strand augments the measurement of political risk with data that stem 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 keywords and their corresponding attitude and tone. One prominent example is the work of Baker et al. [8] 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 following, we describe the variables we assign to political risk and their respective construction in more detail. They are summarized in Tab. (3.6), appendix. Baker et al. [8] provide 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 German BUND to be "risk-free" and, thus, subtract it from this series, such that we obtain a euro area government bond premia.
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. We refer to Garcia-de Andoain and Kremer [22] for a detailed description of this variable.
Unfortunately, given that the aforementioned CDS are only available since 2008 onward, we do not want to shorten our sample and, thus, do not include them in our

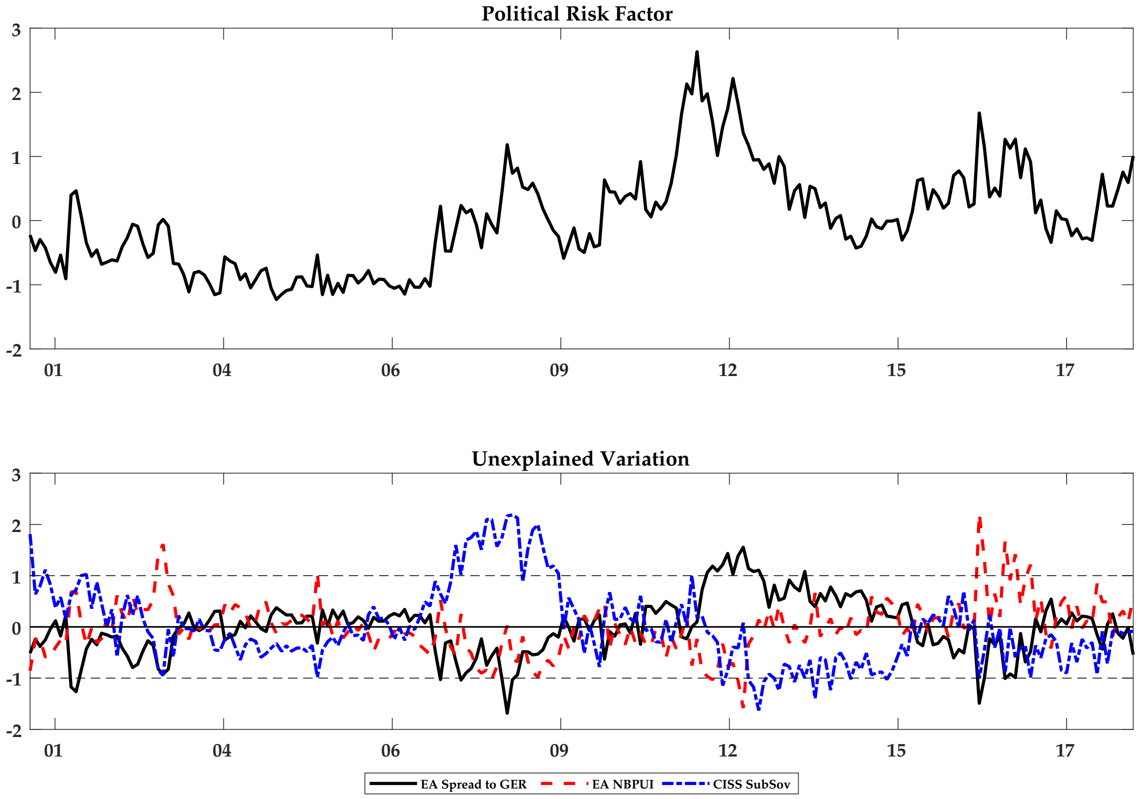


Figure 3.4: First principal component, referred to as Political Risk Factor (PRF), of variables in Tab. (3.6) (upper picture) and residuals $\epsilon_{t\times n}$ of variable movement that is not explained by the common component (lower picture).

analysis. The estimated political risk factor is displayed in Fig. (3.4), amended with the residuals of the variables involved in its estimation.

3.3.3 Financial Market Risk

Our third and last category is financial risk, where we differentiate between various aspects. We use subindices of the CISS[8] to either capture stock 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.

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

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 begun to counteract the turmoils of the 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 funding, i.e. the supply side, are the various (Targeted) Longer-Term Refinancing Operations ((T)LTRO), offered to banks by the ECB. Hikes in the Marginal Lending Facility (MLF) that indicate high liquidity demand are included, too. In addition, excessive usage of the deposit facility (DF) can be interpreted as money market lending side risk. To correct for the conventional conduction of monetary policy that, in particular, dominates pre-2008 periods, we subtract the MF and isolate the extraordinary nature of ECB's policy since 2008.[9] Thus, our variable takes the form

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

and is depicted in Fig. (3.23), appendix, for the sake of illustration. A detailed description of the variables can be found in Tab. (3.7), 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[10] provided by the ECB. Since we think that this variable has to be assigned to systematic risk, we do not consider it within this paper. Nevertheless, we again see the challenge to clearly differentiate among various concepts and types of the phenomenon risk.

The resulting financial risk factor and the respective residuals of the used variables can be found in Fig. (3.5). The factor looks quite similar to the Banque de France's FCI for the euro area, suggested by Petronevich and Sahuc [34]. Their index is estimated via daily data, also with a PCA approach. It sums up information from 18

[9]Note that we cannot account for the introduction of e.g. full allotment procedures or altered requirements for eligibility of assets since 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 side, 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.

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

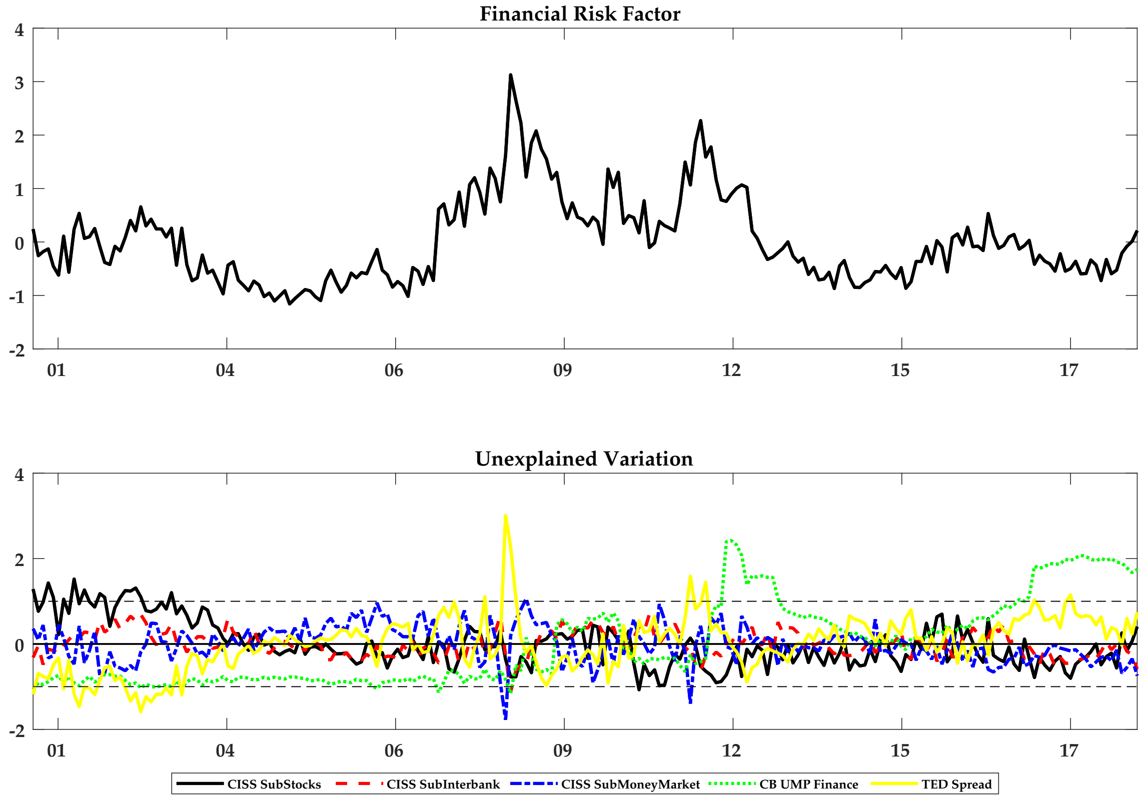


Figure 3.5: First principal component, referred to as Financial Risk Factor (FRF), of variables in Tab. (3.7) (upper picture) and residuals $\epsilon_{t\times n}$ of variable movement that is not explained by the common component (lower picture).

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. (3.6). We invert our macroeconomic risk factor for a better interpretation because this type of risk is high when our factor that tracks it is low, and vice versa. The resulting estimates mirror-image the dominating patterns of various crises in Europe quite well. Macroeconomic risk follows the Great Recession and, to a smaller extent, 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

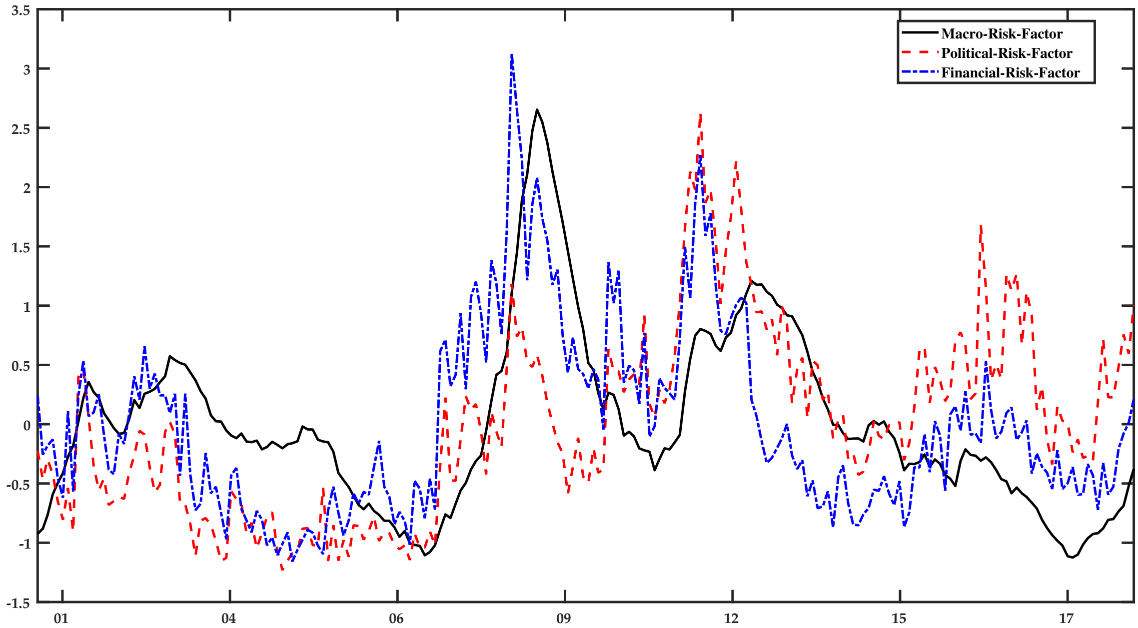


Figure 3.6: Estimated risk factors: MRF (black-solid), PRF (red-dashed), and FRF (blue-dotted).
Notes: The MRF deviates from Fig. (3.3) because we inverted it for ease of interpretation.

current edge. It is lowest 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 extent, severe distortions in European financial markets until the abate of the European Sovereign Debt Crisis in mid-2012.

Note that all three risk factors have peaked 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 more appealingly in Sect. (3.5.1).

3.4 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 low 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 [3]. The following subsections describe our model and estimation methods.

3.4.1 Data and Model

In our model, we incorporate the three mentioned factors, a short-rate and one of the assets mentioned in Sect. (3.2). Hence, our five-variable TVAR model has the reduced-form notation

$$\begin{aligned} Y_t = & \left[c_1 + A_1(L)Y_{t-p} + B_1^{-1}\varepsilon_t\right] \otimes S_t \\ & + \left[c_2 + A_2(L)Y_{t-p} + B_2^{-1}\varepsilon_t\right] \otimes (1 - S_t). \end{aligned} \tag{3.9}$$

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 (SR), we use EONIA[11], our PRF, and the FRF. Moreover, we include the four assets presented in Sect. (3.2) separately. Equity indices enter in logs*100, yields in percentage points. Thus, Y_t takes the form

$$Y_t = [MRF_t \; SR_t \; PRF_t \; FRF_t \; Asset_{i,t}]'. \tag{3.10}$$

c_i are row vectors of constants, $A_i(L)$ 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. (3.11), our model switches with a delay d across regimes if a threshold z^* is surpassed.

$$S_t = \begin{cases} 1, & \text{if } z_{t-d} < \; z^* \text{ (”low-risk regime”)} \; \rightarrow \text{Regime 1} \\ 0, & \text{otherwise (”high-risk regime”)} \; \rightarrow \text{Regime 2} \end{cases}. \tag{3.11}$$

Using this type of model, we can take into account the varying degree of correlation among different types of risk during, for instance high-risk periods. As we will see in Sect. (3.5.1), different risk-regimes coincide. The VAR coefficients of our two distinct regimes can capture these changing relationships.

Moreover, Eq. (3.10) also reflects the order of our baseline, lower-triangular identification scheme via a 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 can capture the contemporaneous interdependencies between the variables and obtain

[11] For periods characterized by the ZLB, EONIA is augemented with the shadow-short-rate by Krippner [33]. The robustness section discusses the usage of an alternative shadow-short-rate provided by Wu and Xia [28].

orthonormal shocks we are interested in later on. Further technical details regarding model estimation are lined out in Sect. (3.4.2). We justify this scheme by the following considerations: macroeconomic variables are inert and only react to own shocks contemporaneously. To pursue its mandate, the central bank aims at controlling short-rates to ultimately influence economic performance. Hence, we assume that macroeconomic innovations and own shocks drive short-rates. 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 be 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 all model variables within the same period. We alter this identification scheme in Sect. (3.6). There, we apply two alternative orders.

3.4.2 Estimation

We estimate the model using Bayesian methods, very similar to Alessandri and Mumtaz [3], chapter 3.3.[12] For comparability reasons across the large set of models[13] 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^*.[14] Furthermore, we prior believe that z^*_{init} is around its median and allow a quite loose variance $\sigma^2_z = 10$. We think that this loose prior for the variance is appropriate because we want to take into account that the often volatile phenomenon risk is reflected by fat tails of the risk variables' distribution. The priors for our 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 $\mathbf{a}_1 = \mathbf{a}_2$, such that we prior assume no state-dependent differences within our model. We limit the value

[12] We thank Blake et al. [13] for providing very helpful codes that are the backbone of our estimation procedure.

[13] 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 the sake of comparability across them, we initially calibrate them all the same.

[14] In Alessandri and Mumtaz [4] d is estimated as well, with the FCI of the Chicago Fed as their 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. We also tested $d = 0$ for all models presented in this paper. Major findings remain unchanged.

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 [15]. 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 randomly generated 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 lower-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 an impulse response analysis during the following 2,000 iterations. We obtain a lower-triangular matrix B_i from Σ_i. This matrix is then multiplied with the estimated reduced-form VAR coefficients $A_i(L)$ and $B_i^{-1}\varepsilon_t$, such that $B_i\Sigma_iB_i' = I$ 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 e.g. in Koop et al. [32]. 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 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 S_t 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. (3.12), for randomly chosen points in time to simulate impulse response functions.

$$IRF_{i,t,t+h} = E\Big[Y_{t,t+h}|\Theta_i, z^*, d, u\Big] - E\Big[Y_{t,t+h}|\Theta_i, z^*, d\Big], \text{ for } h = 0, ..., 30. \quad (3.12)$$

These two conditional expectations differ only by the dynamics induced by a shock vector u[15] that enters the first part of Eq. (3.12). 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

[15] 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.

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 [30].
With this modeling, we can take into account that the regime-switch within our model over our sample can endogenously account for the fact that short-rate shocks affect not only 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.

3.5 Regime-Dependent Transmission of Monetary Policy Shocks

To get a better understanding of 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 crises periods in Europe. Next, we subsequently asses the impact of monetary policy shocks on the various assets for our threshold variables MRF, PRF, and FRF. Further on, we will refer to a low-risk regime when the indicator variable is below the estimated threshold of the respective variable, otherwise, we are in a high-risk regime, as stated in Eq. (3.11). We assume in all cases a one percentage point change in the short-rate and its impact on the different assets, conditional on the respective regime. The impulse response functions for high-risk regimes are red-shaded while the impulse response functions for low-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.

3.5.1 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. (3.7) to Fig. (3.10) 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 low 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. (3.7) to Fig. (3.10), we can see that after the dot.com-bubble burst and before the outbreak of the Great Recession there was a prolonged period of low macroeconomic risk. Moreover, we see that this type of risk skyrockets during the disruptive events of this outstanding crisis. Again, it follows a short period of low 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 low-risk-state until the current edge.

The second column of Fig. (3.7) to Fig. (3.10) contains the threshold and regime-switching propensities when political risk is used as the threshold variable. Before the outbreak of the Financial Crisis, there were prolonged periods of low 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 low-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 low financial risk in the third column of Fig. (3.7) to Fig. (3.10). It stands out that we see a quite long period of high financial market risk, that starts with the Financial Crisis and prevails until the end of the European Sovereign Debt Crisis in 2012. During this period, we never drop back into a low-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 "Whatever it takes" statement in July 2012, 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 low-risk states. This indicates elevated uncertainty about financial stability in European financial markets.

As our binary variable, which indicates the respective regimes, switches frequently in the models with the FRF as threshold, concerns arise about the sharp "jump-like"

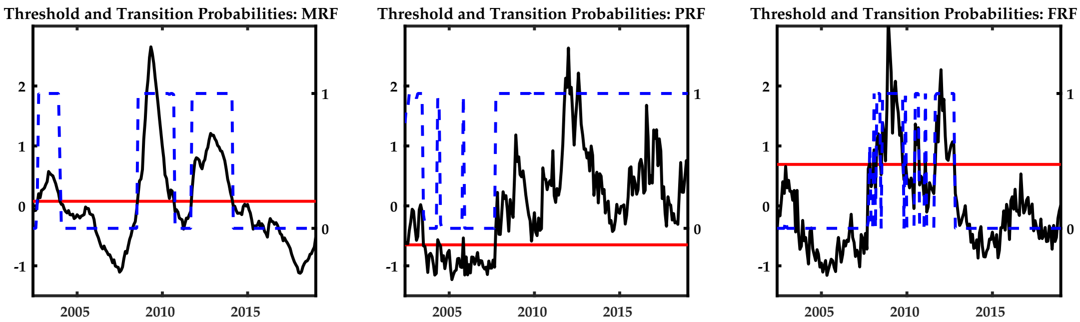


Figure 3.7: TVAR models with ESBanks.

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).

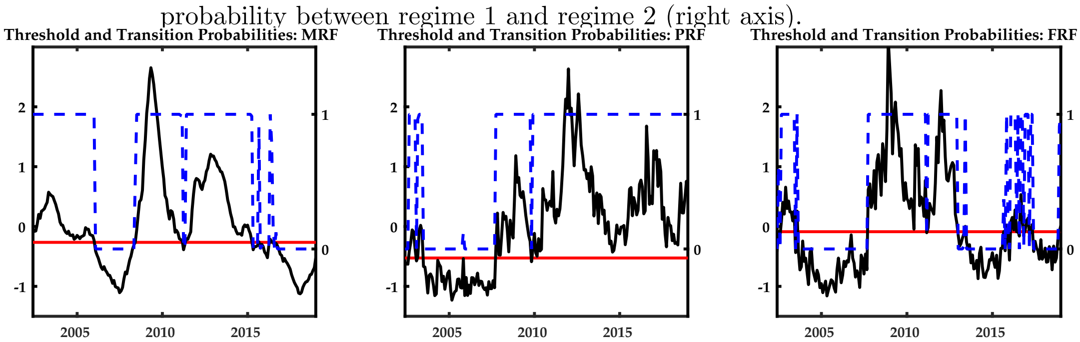


Figure 3.8: TVAR models with ESIndustrials.

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).

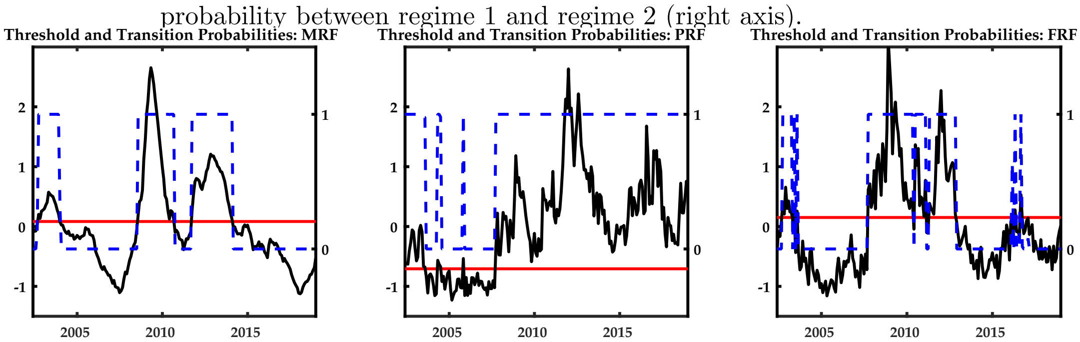


Figure 3.9: TVAR models with CorpBond10YAA.

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).

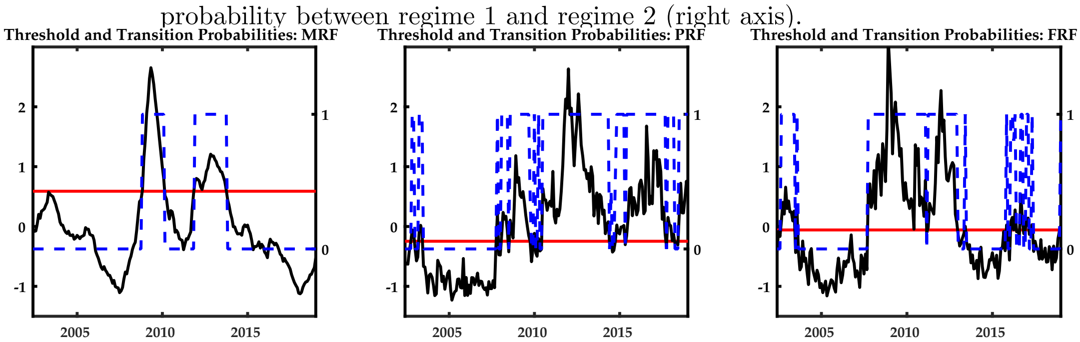


Figure 3.10: TVAR models with CorpBond7-10YHY.

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).

switches between states within a short period. In the appendix, we present an alternative approach to our binary transition setup that stems from a smooth-transition function which is depicted in Fig. (3.28). Incorporating this transition function into our VAR framework and deriving impulse response functions, as in Auerbach and Gorodnichenko [7] 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. (3.3), one possible problem is that different types of risk are interconnected, especially during crises periods. We can see this in Fig. (3.7) to Fig. (3.10) 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 simultaneously high[16] at sample point t, and 0 otherwise:[17]

$$ARO_{i,j,t}^{asset} = \begin{cases} 1, & \text{if } \mathrm{S}_{i,t} = 0 \wedge \mathrm{S}_{j,t} = 0 \text{ with } i,j \in \{MRF, PRF, FRF\}, \quad \forall i \neq j \\ 0, & \text{otherwise.} \end{cases} \tag{3.13}$$

Fig. (3.24) to Fig. (3.27) 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. In contrast, we only have sporadic periods of simultaneous skyrocketing of more than one type of risk at the beginning and 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 distinct delimitation of specific risks during extraordinary crisis periods hard.

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) for high-risk regimes is constructed by dividing the sum of the different AROs by the sample length, corrected for the lag-length of the

[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 z_t.

model, p:

$$RRO_{i,j}^{asset} = \Sigma_{t=2002M4+p}^{2018M1} ARO_{i,j,t} \times (nobs - p)^{-1}, \text{ with } p = 1 \tag{3.14}$$

The results are listed in Tab. (3.1) to Tab. (3.4). 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 lower-triangular block.

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

Table 3.1: RRO between different models with ESBanks.

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

Table 3.2: RRO between different models with CorpBond10YAA.

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

Table 3.3: RRO between different models with ESIndustrials.

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

Table 3.4: RRO between different models with CorpBond7-10YHY.

Overall, we can see that the results are quite similar across the models with their distinct RROs. Nonetheless, there seems 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 model averaging.

3.5.2 Macroeconomic Risk and the Transmission of Monetary Policy Shocks

Fig. (3.11) shows the reaction of our assets in states of high (red area) or low (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 differences for the various assets. The response of ESIndustrials, Fig. (3.11 (a)), dies out faster and is (insignificantly) less sensitive to short-rate shocks in the low-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 low-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 monetary policy has lower (real) impacts in recession periods, i.e. when our MRF is high[18]. Tenreyro and Thwaites [37] line out that the impact of monetary policy shocks on real activity is weaker during business cycle downturns. Moreover, Aastveit et al. [1] find that monetary policy has lower 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 these findings. On the contrary, we find that especially risky junk-bond yields react to a much larger extent when macroeconomic risk is high. We will discuss this finding below.

For ESBanks, Fig. (3.11 (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 low-yield environment, as it is typical for business cycle downturns in general and that exists in particular within the euro area since the European Sovereign Debt Crisis, bank equity seems to benefit from (unexpected) interest hikes. According to Ampudia and Van den Heuvel [5] bank equity can benefit from unexpected hikes in the policy rates if banks operate within a near-zero interest rate environment for a prolonged period, as they boost banks' margins. This can be a possible explanation for this at a first glance counter-intuitive finding, as economic slack and a sharp decline in short-rates as well as a prolonged period of near-zero policy rates go hand in hand in the euro area since the Financial Crisis.

Corporate yields, Fig. (3.11 (c) & (d)), show interesting patterns 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 eight 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 low-macro-risk environment. This also fits into the finding of Tenreyro and Thwaites [37]. The authors line out that during recessions,

[18]Note that we have inverted this variable in Sect. (3.3) for ease of interpretation.

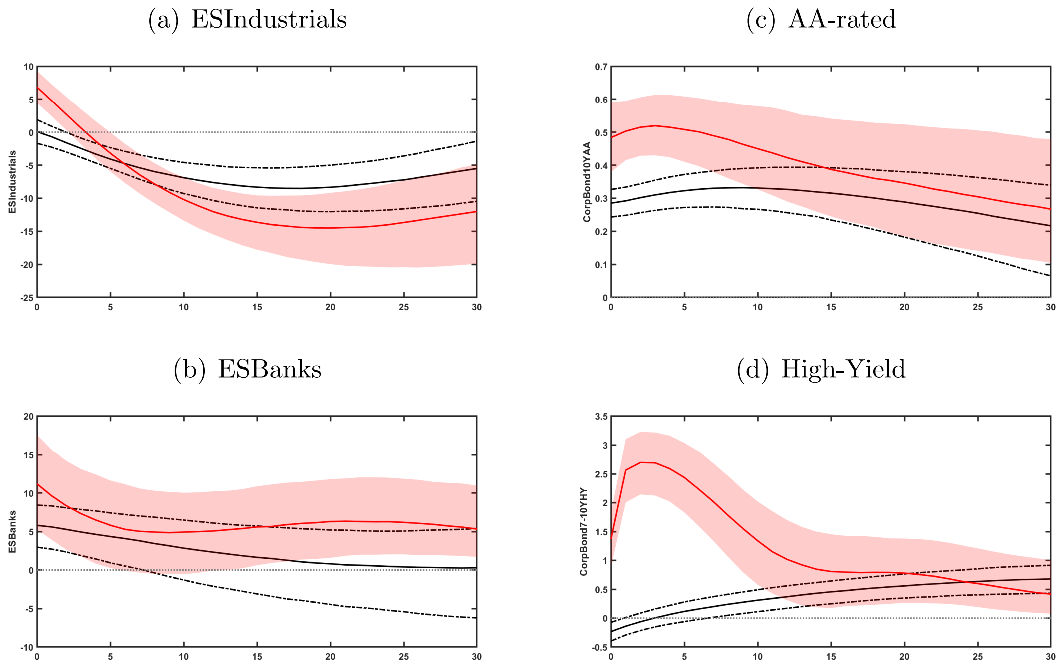


Figure 3.11: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the MRF.

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

the external finance premium, as it is reflected by the Excess Bond Premium (EBP) in Gilchrist and Zakrajšek [23], 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.

3.5.3 Political Risk and the Transmission of Monetary Policy Shocks

Fig. (3.12) shows the reaction of assets in states of high or low political risk when facing a restrictive one percentage point short-rate shock. In periods of low political risk, we see that ESIndustrials, Fig. (3.12 (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, which 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.

Turning to the reaction in high-risk regimes, we see that equity is, in general, less sensitive to yield shocks, compared to low-risk regimes. This could be an indication that during 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, which is a counter-intuitive finding. 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 slower in a high-risk environment, compared to a low-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 dampen 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 regimes are quite similar for the horizon under consideration.

3.5.4 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 low financial risk, Fig. (3.13), we again see very diverging pictures between high-risk or low-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 low interest rates, similar to the setup when macroeconomic risk determines the regimes. Recall that the high-risk regimes for our model with ESBanks, as depicted in Fig. (3.7), concentrate around the Financial Crisis, the European Government Debt Crisis and around the year 2016. As outlined in e.g. Hayo et al. [26] or Claessens, Coleman and Donnelly [17],

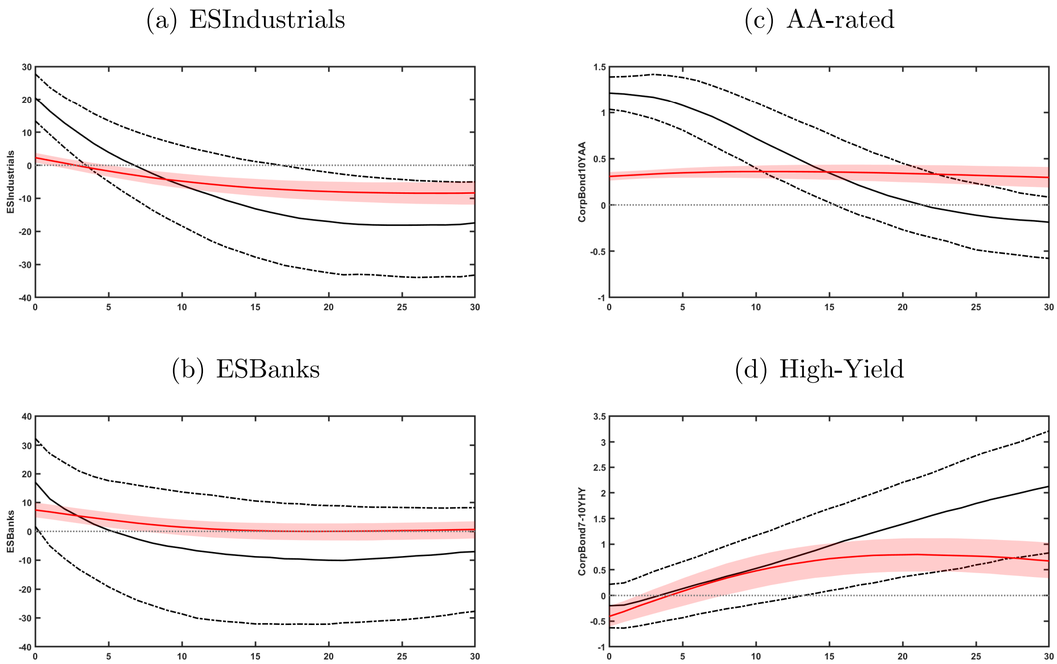


Figure 3.12: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the PRF.

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

bank margins deteriorate in long-lasting low 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 field 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 curious pattern. On the one hand, a restrictive short-rate shock can be interpreted as a signal for a 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 [35], who finds that the transmission of monetary policy is stronger during periods of high financial stress in the US. Using a local projection framework to elaborate the effects of monetary policy shocks on economic activity and financial variables,

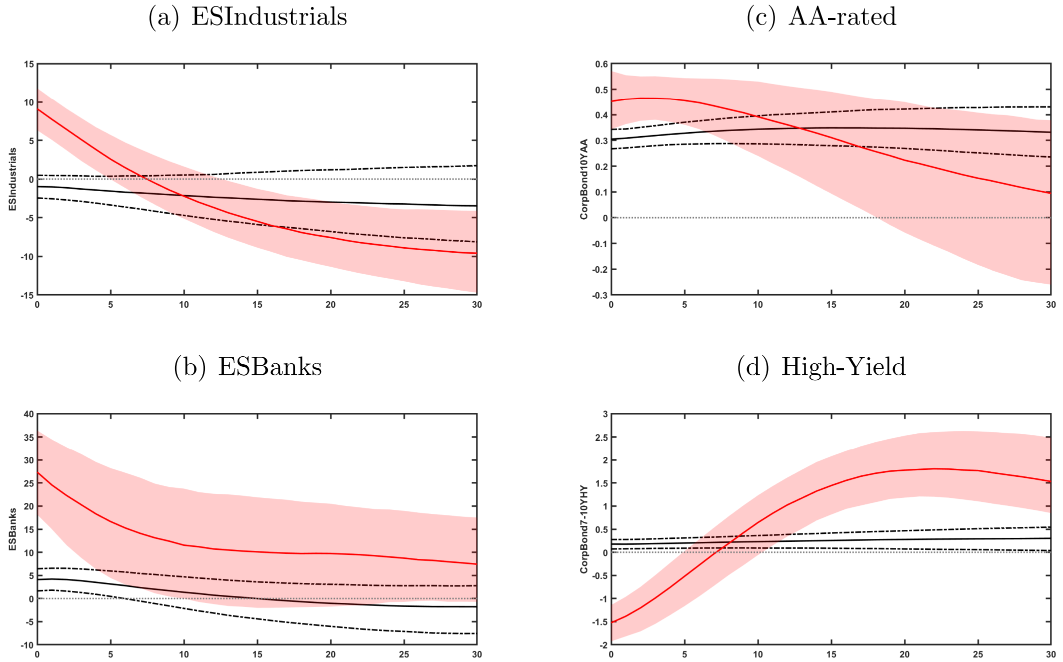


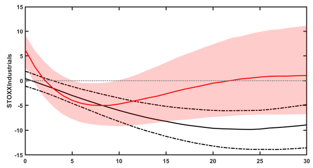
Figure 3.13: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the FRF.
Notes: Median responses and 16^{th} and 84^{th} percentiles of high-risk regimes (red-shaded) and low-risk regimes (black lines).

the author measures financial stress with the EBP of Gilchrist and Zakrajšek [23] which in turn is high for non-investment-grade corporate bonds.

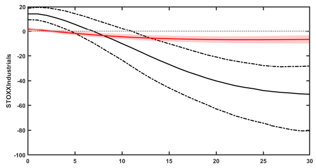
3.6 Sensitivity Analysis

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 lower bound of investment-grade classification, also with 10-year maturity). Additionally, we incorporate an alternative shadow-short-rate provided by Wu and Xia [28]. 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

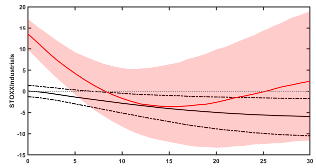
(a) Threshold variable: MRF



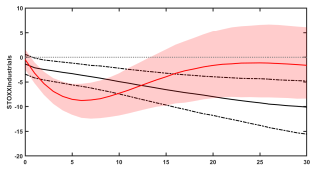
(c) Threshold variable: PRF



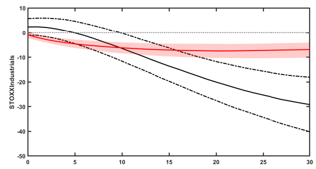
(e) Threshold variable: FRF



(b) Threshold variable: MRF



(d) Threshold variable: PRF



(f) Threshold variable: FRF

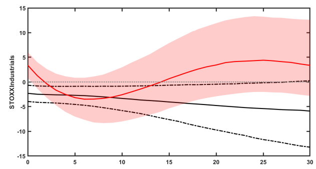


Figure 3.14: Impulse response functions of STOXXIndustrials to a one percentage point shock in the short-rate. The upper row stems from models estimated with Krippner Shadow Rate, the bottom row stems from models with Wu and Xia Shadow Rate.

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

various models and their overlapping properties.[19] Instead, we focus on impulse response functions. Nevertheless, the results are available on request.

3.6.1 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. (3.14) 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-short-rate provided by Krippner [33] or by Wu and Xia [28]. Equity of European industrial firms is, in general, affected negatively in the long-term perspective and is less sensitive to monetary policy surprises if we are in high-macroeconomic- or high-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. In Fig. (3.15) we can see the reaction of STOXXBanks for models with

[19] Note that 18,000 of the 20,000 iterations are identical, as they all stem from the same reduced-form estimation of the model, only the last 2,000 iterations can impact the indication of regimes.

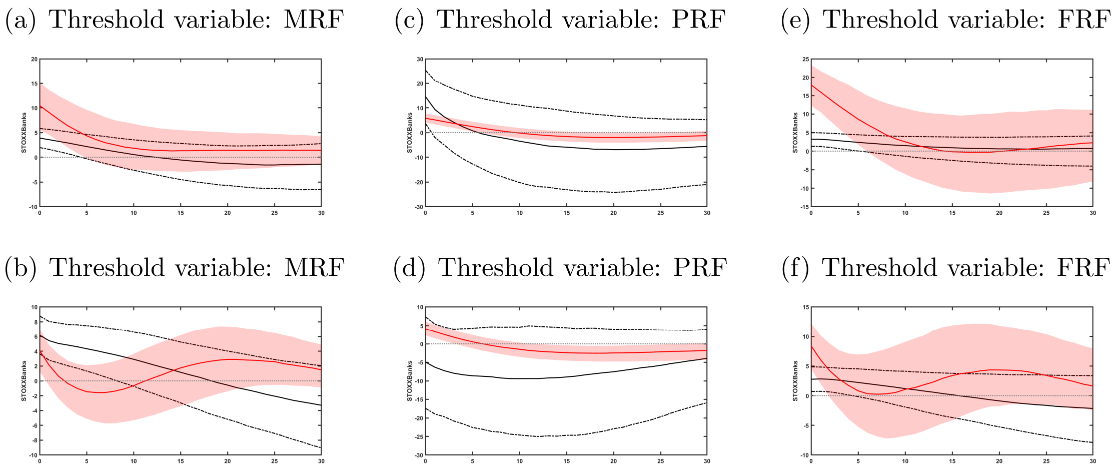


Figure 3.15: Impulse response functions of STOXXBanks to a one percentage point shock in the short-rate. The upper row stems from models estimated with Krippner Shadow Rate, the bottom row stems from models with Wu and Xia Shadow Rate.

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

various threshold variables and the two alternative shadow-short-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 [28] shadow-short-rate, (Fig. 3.15, (b)), where the positive reaction is higher in the regime of low macroeconomic risk.

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 at a rating class that marks the lower end of investment-grade and, thus, lies in between the former two: BBB-rated corporate bond yields with 10-year maturity.

Fig.(3.16) contains the respective impulse response functions. If macroeconomic risk is our threshold variable, we see notable differences across the two regimes. The pattern looks like a mixture of those presented in Fig. (3.11, (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. (3.12, (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. (3.13, (c)).

From these additional results, we can conclude that there is a gradual shift in the relevance of different types of risk for different rating classes. The riskier the underlying bond, the more we see pronounced state-dependency 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 to financial risk.

(a) Threshold variabl: MRF (c) Threshold variable: PRF (e) Threshold variable: FRF

(b) Threshold variable: MRF (d) Threshold variable: PRF (f) Threshold variable: FRF

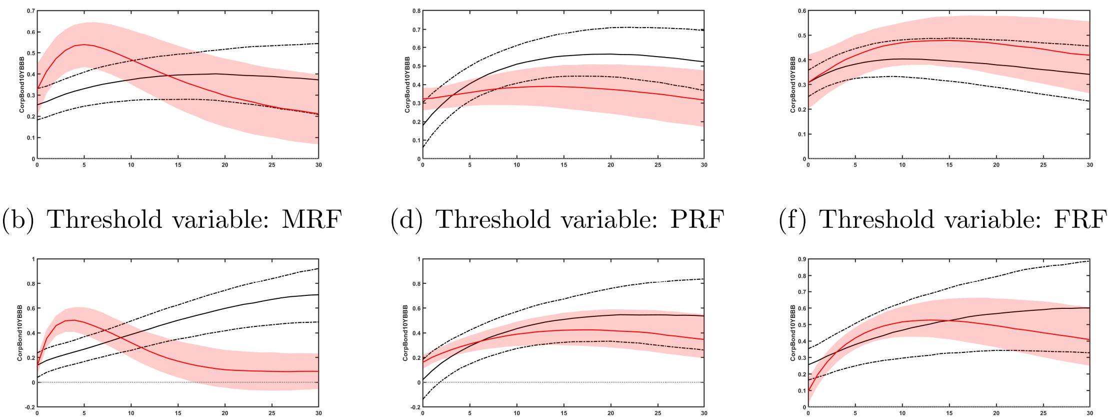


Figure 3.16: Impulse response functions of BBB Corporate Bond 10-year yield to a one percentage point shock in the short-rate. The upper row stems from models estimated with Krippner Shadow Rate, the bottom row stems from models with Wu and Xia Shadow Rate.

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

3.6.2 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.

$$\text{Order 2: } Y_t = [MRF_t \; FRF_t \; SR_t \; PRF_t \; asset_{i;t}]'. \tag{3.15}$$

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 the need to maintain 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:

$$\text{Order 3: } Y_t = [MRF_t \; FRF_t \; PRF_t \; SR_t \; asset_{i;t}]'. \tag{3.16}$$

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 take the possibility into account that policy actions of the ECB are contemporaneously impacted by political risk. Such considerations hold especially during the European Sovereign Debt Crisis. Assets are again ordered last to be impacted by all other variables within the same period.

In the following, 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. (3.17) and Fig. (3.18) show the reaction of our assets discussed in Sect. (3.5) 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 short-rate. All assets, except ESIndustrials, show the same qualitative behavior in both alternatives. ESIndustrials, on the other side, reacts less strongly during stages of increased macroeconomic risk when focusing on a longer horizon.

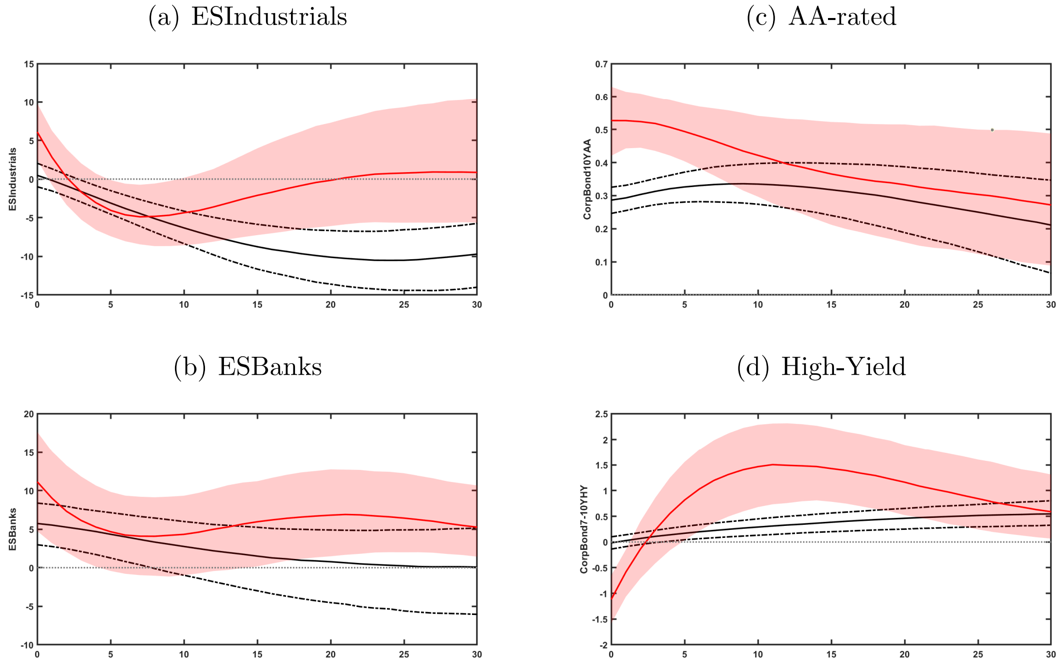


Figure 3.17: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the MRF, identification obtained from order 2.

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

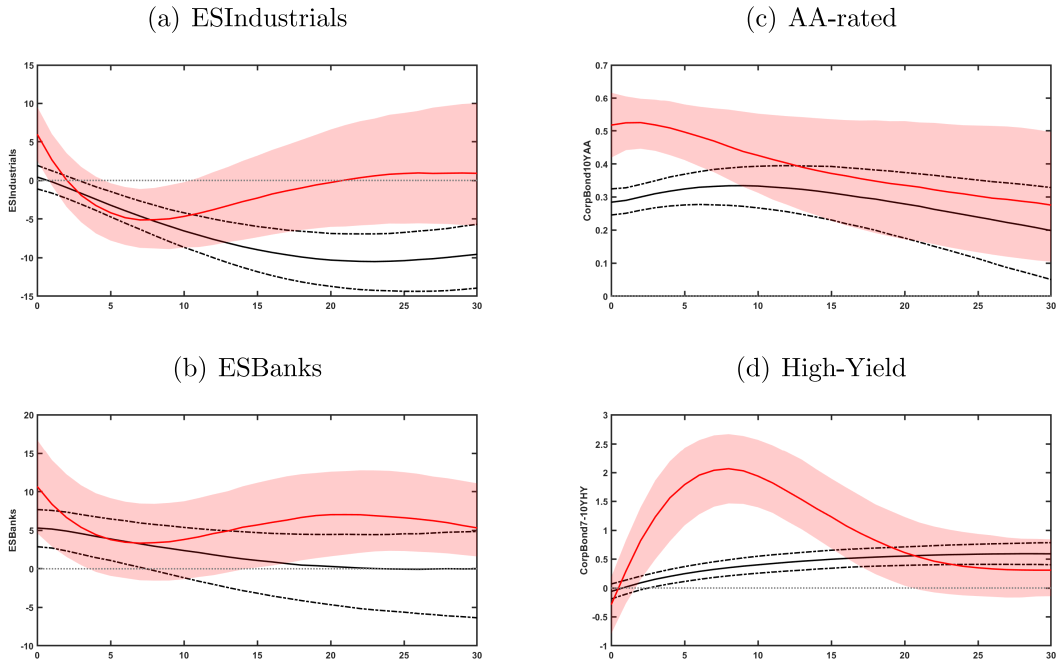


Figure 3.18: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the MRF, identification obtained from order 3.

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

Political Risk and Transmission of Monetary Policy Shocks

Fig. (3.19) and Fig. (3.20) contain the reaction functions of the respective assets to a one 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 shown in Fig. (3.21) and Fig. (3.22). In both ordering schemes, we see an outstanding positive effect of short-rate hikes on equity during regimes of high financial risk. Again, bank stocks show a positive reaction, even during periods of low financial tension. While investment-grade bond yields are impacted quite similar, we see a divergent pattern for low-grade bond yields.

3.7 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 vector-autoregressions as well as the incorporation of state-dependency, i.e. high- or low-risk regimes. Nevertheless, we emphasize the caveat of "correct" risk delimitation and illustrate how

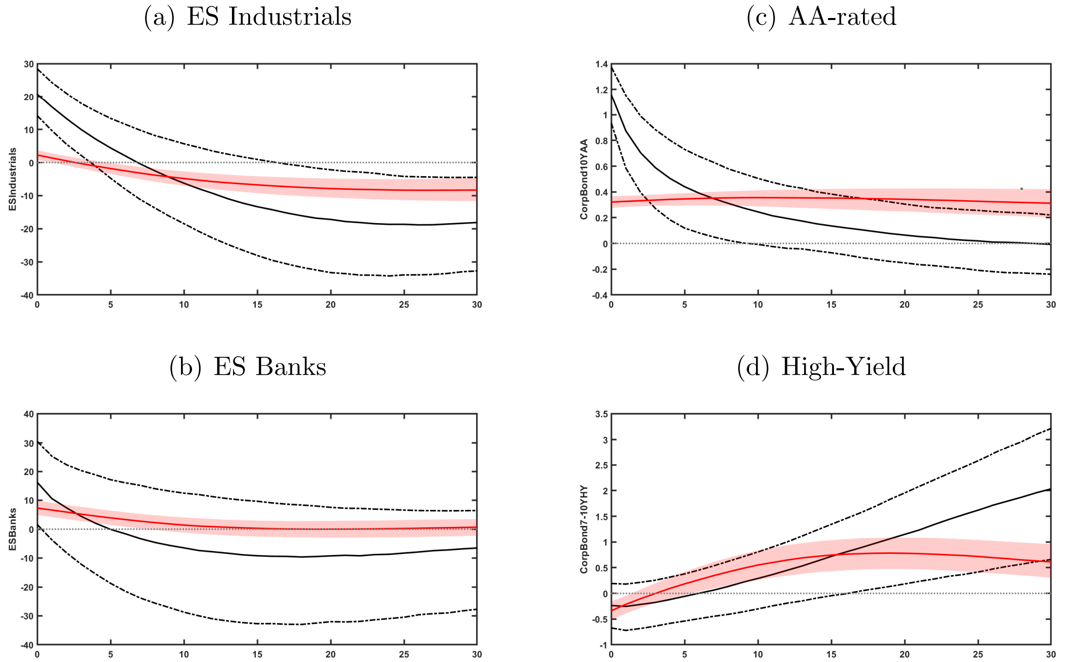


Figure 3.19: Impulse response functions of assets to a 1 percentage point shock in the short-rate, threshold variable is the PRF, identification obtained from order 2.

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

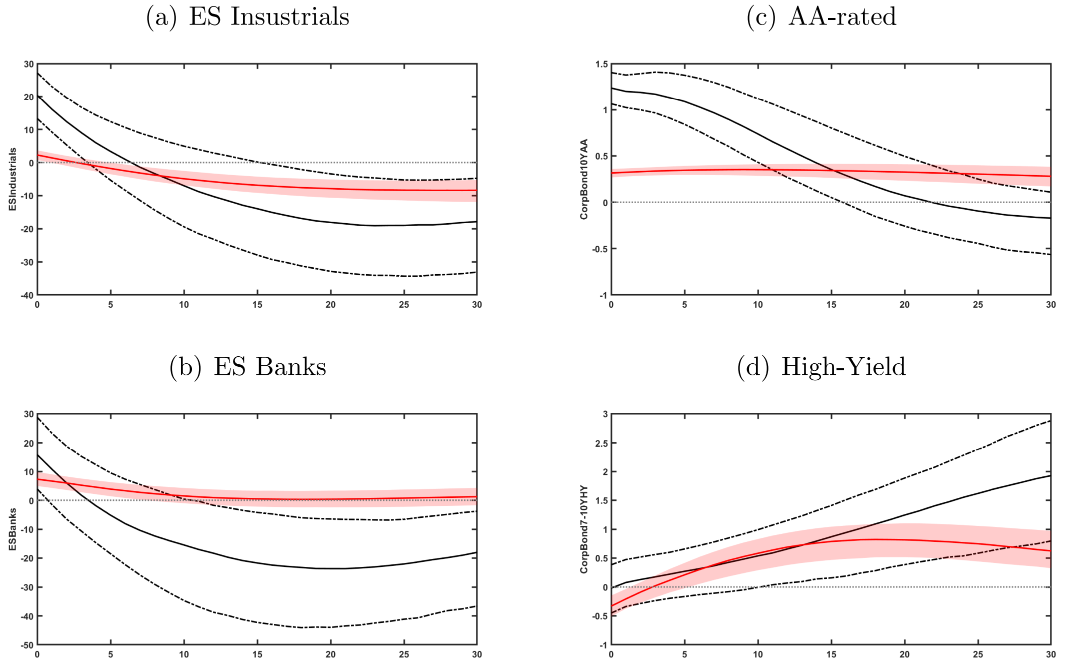
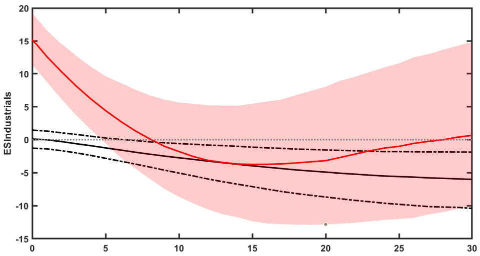


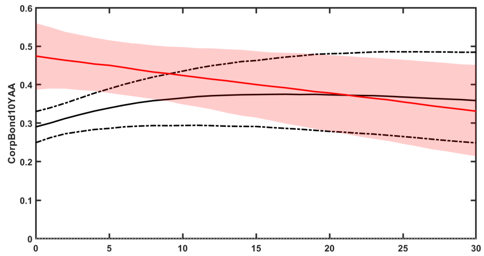
Figure 3.20: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the PRF, identification obtained from order 3.

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

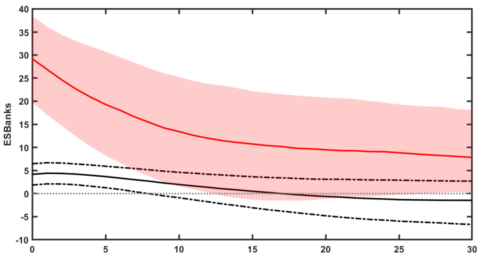
(a) ES Industrials



(c) AA-rated



(b) ES Banks



(d) High-Yield

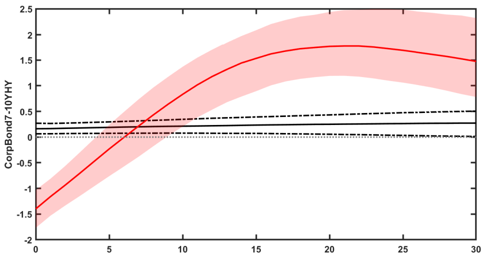
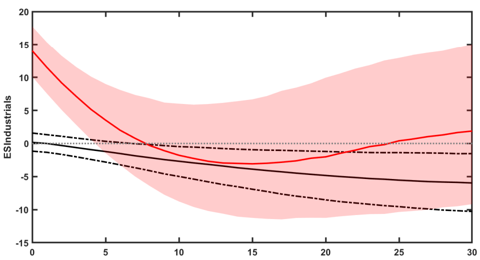


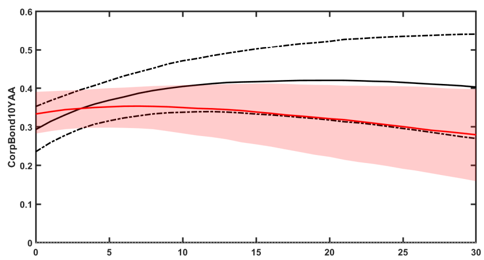
Figure 3.21: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the FRF, identification obtained from order 2.

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

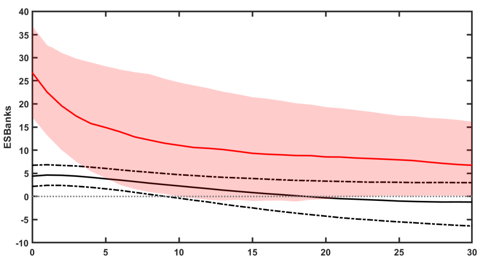
(a) ES Industrials



(c) AA-rated



(b) ES Banks



(d) High-Yield

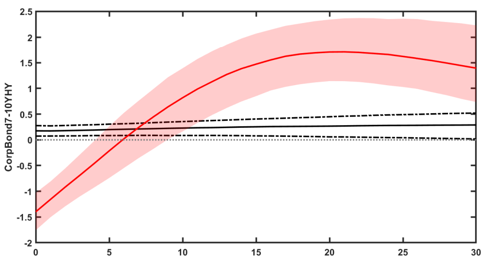


Figure 3.22: Impulse response functions of assets to a one percentage point shock in the short-rate, threshold variable is the FRF, identification obtained from order 3.

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

the indicated regimes overlap for the set of estimated threshold-VAR models.
Analyzing the state-dependent sensitivity of asset prices to a short-rate shock, the impulse responses show that, first, the reaction of asset prices depends indeed on the respective risk-state and, second, that these asset prices are disparately susceptible, depending on the respective risk environments.
We can summarize these differences in susceptibility: if we distinguish between high and low macroeconomic risk, we in general 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 significant positive reactions occur primarily during phases of elevated macroeconomic or financial risk. For non-investment-grade corporate bond yields, we find that their sensitivity 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 low political risk.
From these results, we can conclude for corporate bond yields that there is a gradual shift in the relevance of different types of risk that depends on the respective rating. The riskier the underlying bond, the more we see pronounced state-dependency 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 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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3.8 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	Centre for Economic Policy Research (CEPR)	HLink: click here
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 3.5: 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. [8], Author's calculations	-
Spread EA - GER, in %	none	Datastream, Author's 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 3.6: 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	none	Datastream, Author's Calculations	EMLDEPO,EMEBSMLFA, EMECAEX,EMAREFO
Ted-Spread, in %	none	Datastream, Author's calculations	TRBD3MT,EIBOR3M

Table 3.7: List of variables, their initial transformation, and source that are assumed to be primarily driven by financial market risk.

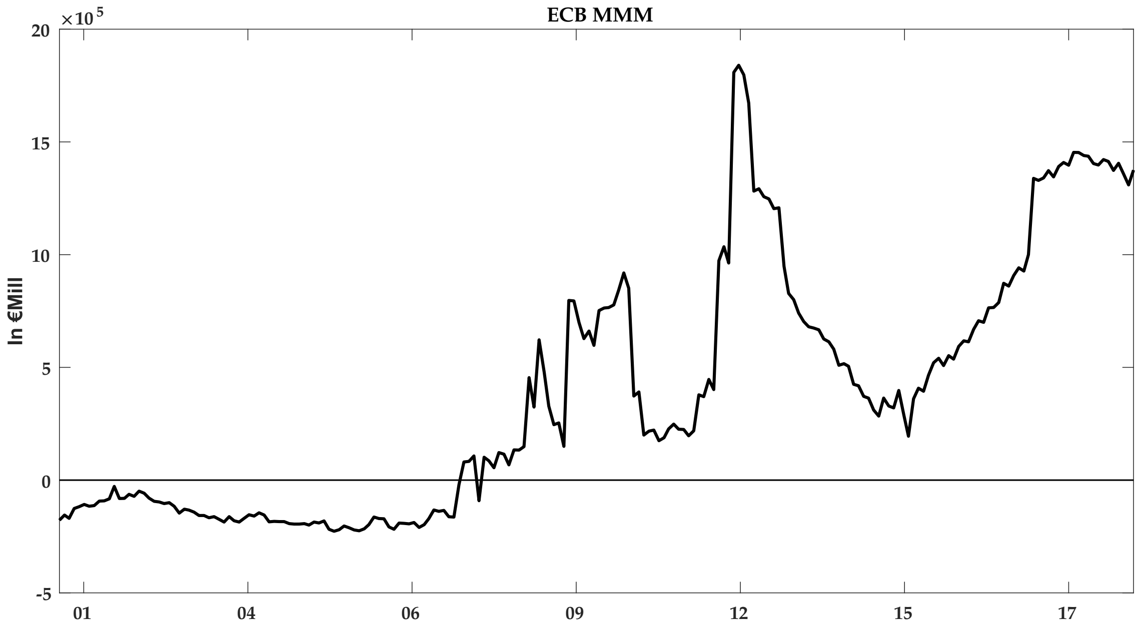

Figure 3.23: Quantitative measure for ECB's programs that are directed towards money market distortions and liquidity provision.

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 3.8: 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 3.9: 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 3.10: 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

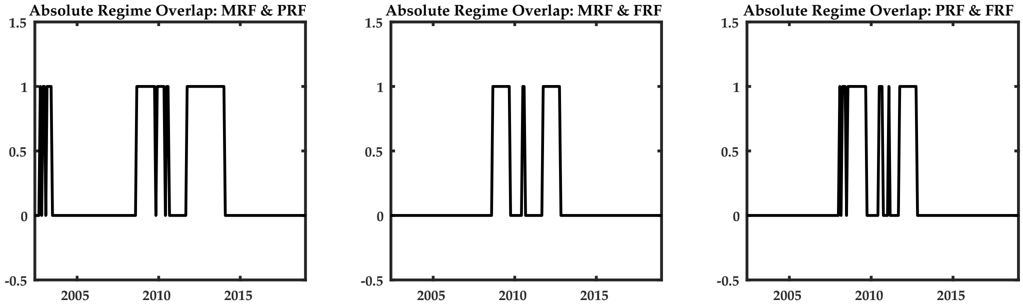

Figure 3.24: Regime Overlap for TVAR models with ESBanks.
Notes: Black-solid is the high-risk regime overlap between MRF & PRF (left), MRF & FRF (middle), and PRF & FRF (right).

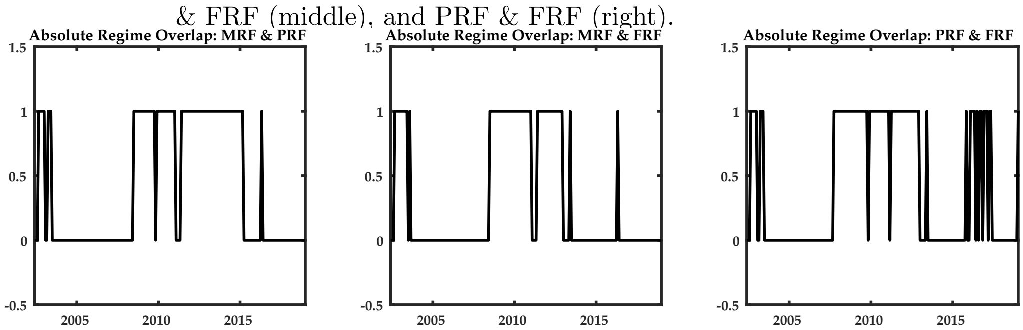

Figure 3.25: Regime Overlap for TVAR models with ESIndustrials.
Notes: Black-solid is the high-risk regime overlap between MRF & PRF (left), MRF & FRF (middle), and PRF & FRF (right).

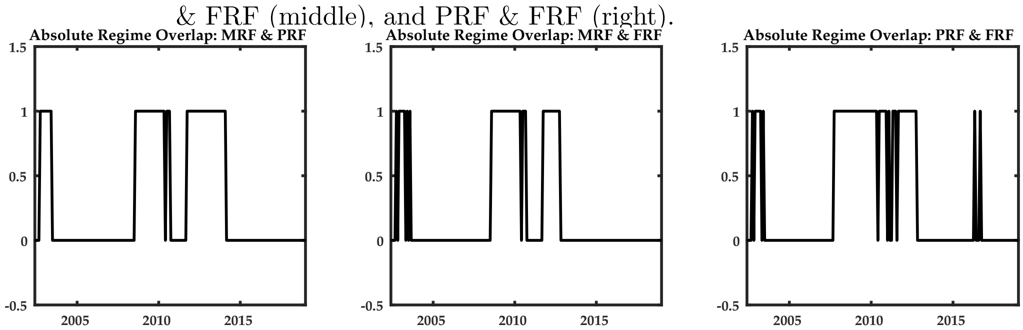

Figure 3.26: Regime Overlap for TVAR models with CorpBond10YAA.
Notes: Black-solid is the high-risk regime overlap between MRF & PRF (left), MRF & FRF (middle), and PRF & FRF (right).

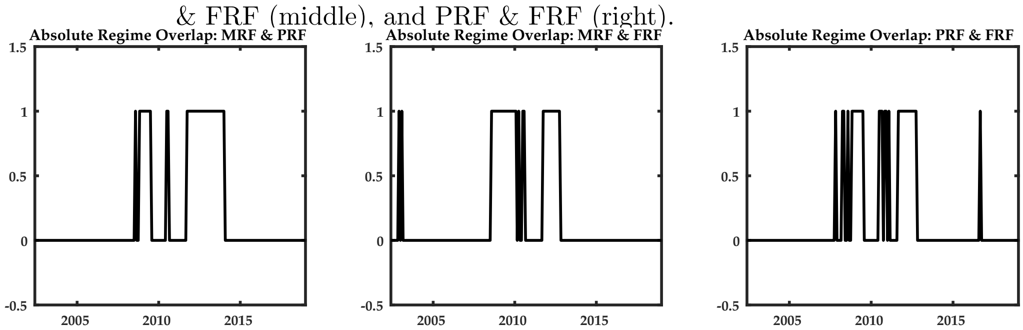

Figure 3.27: Regime Overlap for TVAR models with CorpBond7-10YHY.
Notes: Black-solid is the high-risk regime overlap between MRF & PRF (left), MRF & FRF (middle), and PRF & FRF (right).

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. (3.17). 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:

$$G_t(z_t) = \frac{1}{1 + \exp(-\gamma(z_t - c))}, \quad G_t \in (0, 1) \tag{3.17}$$

For our analysis, z_t equals FRF_t. The transition properties of $G(.)$, i.e. how violently the model switches across regimes, depend on the choice of γ. For $\gamma \to \infty$, we are back in a binary setup, as the transition across states is very sharp, limiting the value space of $G(.)$ to 0 or 1, depending on passing the shift parameter c. In contrast, for $\gamma \to 0$ 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 [7] 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 interested in asymmetric effects of fiscal policy across recessionary or non-recessionary stages, the standardized seven-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, they set $c = 0$. They observe that the US is on average in about 20 percent 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 low-risk regimes. As there exists no universally acknowledged indicator that clearly states when the euro area is in a high or low financial risk state, we use the set of regime estimates from the main section, see Tab. (3.1) to Tab (3.4), right corners, or Fig. (3.7) to Fig. (3.10), 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 assumption of Auerbach and Gorodnichenko [7] 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.

Furthermore, 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 [7]. 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 thresholds 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. (3.28) displays these two slightly different transition functions.

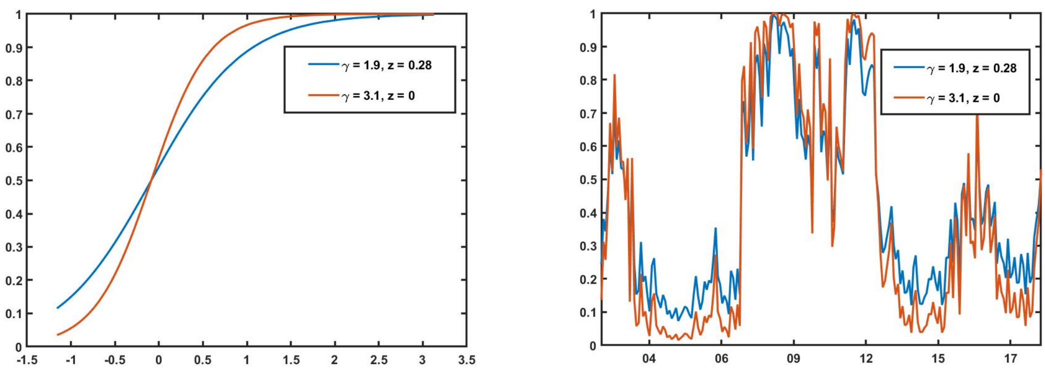

Figure 3.28: The left figure shows the transition functions $G(FRF, \gamma, z)$. The right figure shows the value of the transition functions $G_t(FRF_t, \gamma, z)$, for given γ and z, respectively, over our sample.

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. (3.7) to Fig. (3.10), 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.

4 Moving Closer or Drifting Apart: Distributional Effects of Monetary Policy

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Presenter: Paul Rudel.

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Presenter: Lucas Hafemann.

III. Money, Macro and Finance Research Group (MMF):
49th Annual Conference, 09/2017, London, United Kingdom.
Presenter: Paul Rudel.

[1]We are grateful to two anonymous referees and participants at the 49th Annual Money, Macro, and Finance Research Group Conference for fruitful comments.

Moving Closer or Drifting Apart: Distributional Effects of Monetary Policy

Lucas Hafemann[*,1] Paul Rudel[*,2] Jörg Schmidt[*,3]

The heating debate about increasing income inequality forces monetary policy makers and academia to (re-)assess the nexus between (unconventional) monetary policy and inequality. We use a VAR framework to unveil the distributional effects of monetary policy and the role of redistribution in six advanced economies. While all of them experience an increase in Gini coefficients of gross income due to an expansionary monetary policy shock, only countries with relatively little redistribution display a significant response of net income inequality as well. To examine the underlying transmission channels we take a closer look at the sources of income, i.e. labor and capital income. Our findings suggest that the disproportional surge in capital income is the driving force behind the increase in net income inequality.

Keywords: income inequality, factor income distribution, monetary policy, redistribution,

JEL classification: E24, E25, E52, E64

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4.1 Introduction

"All economic policy-makers have some distributional impact as a result of the measures they introduce - yet until relatively recently, such consequences have been largely ignored in the theory and practice of monetary policy." Yves Mersch (ECB), 2014

The Financial Crisis has set the limit of conventional monetary policy measures for the majority of the advanced economies. To stabilize financial markets and stimulate the economy major central banks around the world steadily lowered their policy rates up to the zero lower bound (ZLB). As this lowering was often not sufficient to fulfill their mandate, the central banks imposed unconventional measures including i.a. large-scale asset purchase programs (LSAP) and forward guidance on policy rates. As a consequence, equity and housing prices increased, while, at the same time, interest rates and returns on savings remained at an all-time low. In public, this constellation strengthened the perception of rising inequality arguing that such measures benefit already wealthy capital owners disproportionately. The public arousal forces policy makers and academia to discuss the distributional consequences of monetary policy.

However, no central bank pursues equality per mandate.[1] Nonetheless, economic key indicators that are within the scope of central banks, like inflation and growth, have distributional effects themselves. For example, Doepke and Schneider [10], Albanesi [3], and Adam and Zhu [2] find that unexpected inflation coincides with higher level of inequality. The analyses by Romer and Romer [23] indicate a positive relationship between inequality and both, average inflation and volatility of nominal GDP growth. Thus, every policy measure that addresses one or both of the key indicators will have inevitably distributive effects.

Still, policy makers might have an intrinsic interest in moderate levels of inequality: Areosa and Areosa [4], Auclert [6], and O'Farrell et al. [20] ascertain that higher levels of inequality coincide with less stimulating power of monetary policy.

There are several mechanisms through which monetary policy may affect the distribution of income and wealth. Since we are interested in the nexus between monetary policy and income inequality, we limit our analyses to the following channels:

The *employment channel*: Labor income is the major earnings source for the vast majority of households. However, high-skilled and low-skilled households respond differently to monetary-policy-induced fluctuations on the labor market. If low-

[1] Also because it is troublesome to measure a (socially accepted) "natural level of inequality". Still, some attempts were made. See for example Rodriguez et al. [22] or Heer and Maussner [12]. Mankiw [16] describes anecdotally, why some inequality is necessary for prosperity.

skilled households are more likely to be affected by unemployment in an economic downturn, monetary stimulus benefits those households disproportionately and alleviates an increase in income inequality.

The *income composition channel*: Households differ in terms of their primary incomes. If monetary policy benefits capital income more than labor income, e.g. through boosting dividends or stock returns, as it can be observed since the introduction of quantitative easing (QE), income inequality will increase because capital income receivers are primary high-income households.

Neither is the transmission of monetary policy to inequality unambiguous, nor the findings in the literature. Mumtaz and Theophilopoulou [18] and Coibion et al. [8] find that contractionary monetary policy shocks increase inequality in earnings, income, and consumption. In their analysis for the US, Coibion et al. [8] draw a number of conclusions. Following a monetary policy shock, wage earnings for those in upper percentiles of the wage distribution recover notably faster than for those at the bottom of the distribution. The total income effect is smaller because low-income households disproportionately rely on transfers which in turn react counter-cyclical. Lansing and Markiewicz [14] and Coibion et al. [8] state that the distributional effects of monetary policy were mitigated by governmental redistribution in the US.[2] In contrast, Davtyan [9] finds evidence for the US that contractionary monetary policy shocks are associated with lower income dispersion in the long-run.

Primarily unconventional monetary policy measures are suspected to be one of the main drivers of increasing inequality in recent years. The argument is that ultra-loose monetary policy disproportionately benefits asset holders because the returns of a broad variety of assets surged due to LSAPs and low long-term yields. The stimulating effect elevated corporate profits faster than employment. Overall, the contribution of unconventional monetary policy measures to increasing inequality is not clear cut and respective research is limited.

Mumtaz and Theophilopoulou [18] gauge an additional effect on inequality from unconventional measures taken by the Bank of England in the aftermath of the Financial Crisis. Adam and Tzamourani [1] find that the ECB's 2012 announced Outright Monetary Transactions program influenced market prices such that the top 5% wealth group benefited disproportionately. Domanski et al. [11] find that wealth inequality in advanced economies has risen since the Financial Crisis. They identify surging equity prices as the key driver.

Our contribution to the outlined controversy is twofold. Cross-country analyses un-

[2] In addition, Ostry et al. [21] show that redistribution can be pro-growth due to positive effects of lower levels of inequality.

veil the role of redistribution in the nexus between (gross and net) income inequality and monetary policy. Data on factor income from national accounts uncover the underlying transmission mechanisms.

We focus on the transmission channels of monetary policy on income inequality, namely the income composition and employment channel. The procedure outlined in Bernanke and Gertler [7] is used to analyze the potential mechanisms that drive the Gini measures after an expansionary 25 basis points (bp) monetary policy shock. Moreover, this work shall expose the role of redistribution. For this task, we choose countries that a) have an independent and autonomous central bank, and b) differ in their scope of redistribution. Thus, our analysis relies on the US, Canada, South Korea, Sweden, the Czech Republic, and Hungary. To incorporate redistributive effects, we examine the impulse responses of both, Gini of gross income (pre-tax, pre-transfers, *Gini gross* hereafter) and Gini of disposable income (post-tax, post-transfers, *Gini net* hereafter).

Figure (4.1) provides an overview of the Ginis for gross (red solid) and net (dotted) income as well as the policy rates (green solid) for the chosen countries. All countries but Sweden show an upward trend in Gini gross. The US, Sweden, and Hungary show the highest levels of gross income dispersion. Concerning net income dispersion, Sweden, the Czech Republic, and Hungary kept their levels in the considered periods while the US, Canada, and South Korea show an increase in the Gini net. Furthermore, the interest rates dropped in all countries.

However, the major findings of our paper are threefold: Firstly, we observe an increase in inequality of Gini gross for all countries included in this paper when facing expansionary monetary policy. Secondly, we find that the effect on the Gini net remains positive for countries with minor redistribution. In contrast to this, countries with high relative redistribution do not face the same positive reaction in their net income inequality. Thirdly, we show that monetary policy is transmitted via overall employment, labor income, and capital income. Moreover, the disproportional surge in capital income is the driving force behind the increase in net income inequality.

The remainder of the paper is organized as follows. First, we introduce our data and methodology. Chapter 4.3 covers the analysis of the nexus between monetary policy shocks and income inequality. In chapter 4.4 we take a closer look at the underlying transmission mechanisms. The conclusion follows after a robustness section.

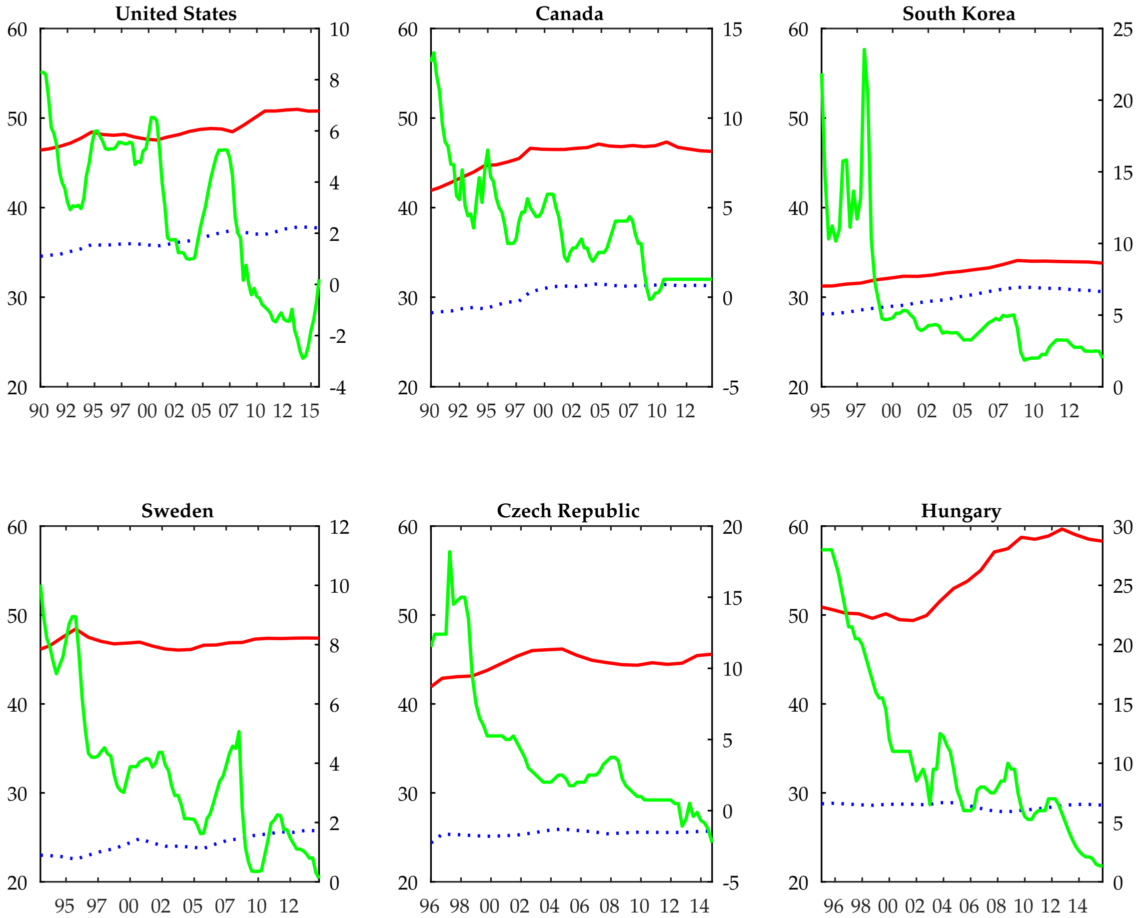

Figure 4.1: Income Inequality and Policy Rates.
Notes: Red solid (blue dotted) line depicts Gini gross (net)left ordinate, in percent. Green solid present key policy rates, in percent, right ordinate.

4.2 Data and Methodology

Before we proceed to our analysis of the nexus between monetary policy and its impact on the distribution of income as well as the underlying channels of transmission, we want to take a closer look at the data and methodology.

4.2.1 Data

The main objective of this paper is to examine the transmission mechanisms through which gross and net income distribution respond to monetary policy surprises and thus, obliquely, the role of governmental redistribution.
On the subject of redistribution, we select among OECD members regarding their relative redistribution.[3]

[3]The relative redistribution is computed as the difference between gross and net income Gini divided by the gross income Gini and multiplied by 100.

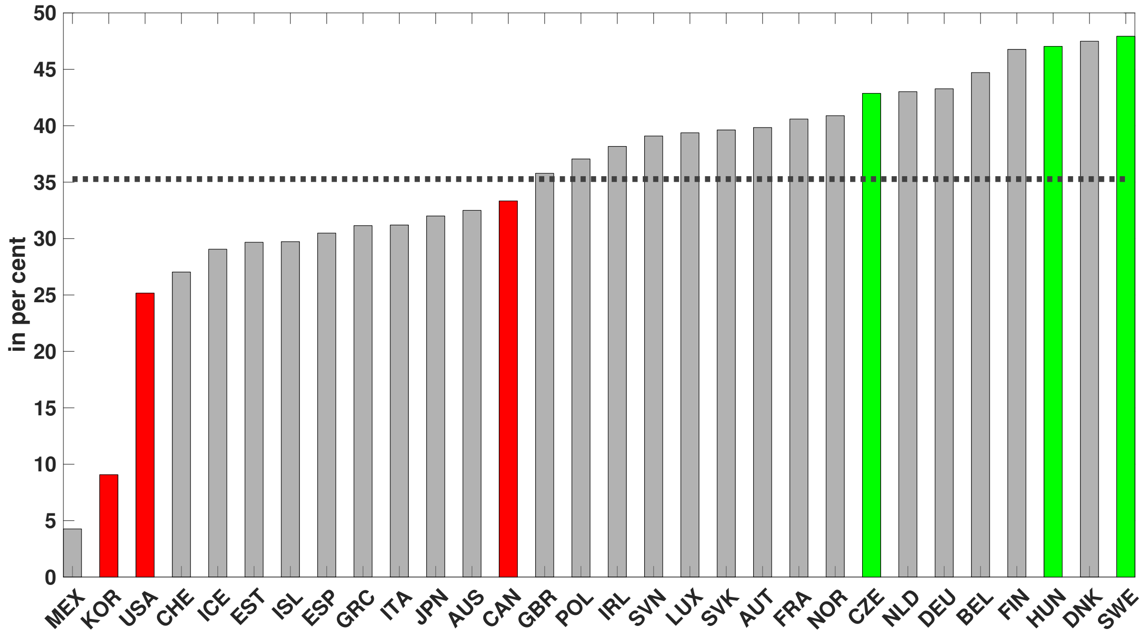

Figure 4.2: Relative Redistribution among OECD Members.
Notes: Relative redistribution is computed as $100 \times (Gini\,gross - Gini\,net) \times Gini\,gross^{-1}$. Dotted line depicts cross-country mean.

Figure (4.2) depicts the average relative redistribution from 1995 to 2015, taken from the Standardized World Income Inequality Database (SWIID). Redistribution among OECD countries varies remarkably. At the upper end, Sweden, Denmark, and Hungary almost halve income inequality through redistribution, i.a. by way of taxes and transfers. In contrast, the US, South Korea, and lastly Mexico are the countries with the lowest relative redistribution.[4] It stands out that predominately European countries show the highest levels of redistribution among OECD members. For example, out of the countries with relatively much redistribution, Canada is the non-European country with the highest relative redistribution: they lower income inequality by 33% through governmental intervention.
To examine the reciprocation of (various measures of) inequality to monetary policy shocks in a meaningful manner, we exclude all countries that are either part of a monetary policy union (i.e. the euro area) or directly peg their currency to others for a substantial period, in other words, have no independent monetary policy.
That said, we are left with Sweden, Hungary, and the Czech Republic as surrogates for highly redistributing countries on the one hand and Canada, the US, and South Korea on the other hand.[5]

[4]Note that little redistribution does not necessarily correspond with a high level of inequality. South Korea, for example, already has a low level of inequality such that there is less need for redistribution to reach some sort of income equality. At the end, it remains a social decision how much redistribution a society desires.

[5]At the first glance, Mexico seems to be a valid candidate, too. In section 4.4 we compare the

In a first step, we want to capture the reaction of Gini coefficients of gross incomes to monetary policy. We then evaluate in how far monetary policy shocks propagate to the dispersion of households' net income. For both exercises, we use the corresponding mean estimators from the SWIID data set, compiled by Solt [26], for all countries included in this paper. Since we use a VAR model with quarterly data, we linearly interpolate all Gini variables.[6]

Finally, we take a look at the transmission channels. Following the idea of Bernanke and Gertler [7], we substitute the Gini coefficients with variables that are affiliated to the transmission mechanisms discussed above. In this respect, we analyze how the total number of employed persons as well as capital and labor income reacts to a monetary policy shock. The data for the channel variables stem mainly from the OECD.[7]

We conduct baseline vector-auto-regressions that (separately) include the inequality measures (i.e. the Gini coefficient or the channel variable) for each of the six countries in our sample, additional to the standard macroeconomic variables real GDP, consumer prices, a short-term interest rate, and the trade-weighted real effective exchange rate (REER). All non-stationary variables enter our model in log-levels. This assures that we take possible (long-run) cointegration relations between the variables into account. For example, Davtyan [9] shows that there is a long-run relationship between monetary policy and inequality. The REER is incorporated because five of the six analyzed countries are small open economies where the exchange rate channel appears to be a relevant monetary transmission mechanism. Data on real GDP and CPI are taken from Datastream. Exchange rates stem from the Bank of International Settlements.[8]

Since we do not exclude periods of financial stress, we control for market uncertainty by including the CBOE Volatility Index (VIX). The VIX enters as an endogenous variable into the US model and as an exogenous variable into the VAR model of the remaining countries.

Our applied short-term interest rates deserve some special attention. We generally prefer the use of money market rates because monetary policy makers aim at the short-term inter-bank refinancing conditions as their intermediate objective. How-

responses of labor-related income and capital income to a monetary policy shock where we ground our analysis on OECD data which are unfortunately not available for Mexico.

[6]One might argue that the variables could be sensitive to altering interpolation methods. We believe that the interpolation method does not alter the results in a notable manner due to the inherent inertia of the variables. Nonetheless, we provide estimates with yearly data and get similar results.

[7]A more detailed description of the respective data is provided in section 4.4.

[8]For the sake of comparability, we include the exchange rate in the US model, although it is not a small open economy.

ever, for Hungary and the Czech Republic, money market data is not available for the considered period. Therefore, we have to use the key policy rate in these two countries.
Furthermore, the ZLB becomes an issue in Canada, the Czech Republic, and the US.[9] For the latter, the interest rate variable is the Wu and Xia [28] shadow rate, available since 2003, and the effective Federal Funds Rate for previous periods. For Canada, we use a shadow interest rate estimated by MacDonald and Popiel [15].[10] Unfortunately, shadow interest rates are not available for the Czech Republic. Hence, we use the euro area shadow rate from Q4 2012 onward because the short term interest rate dropped to 0.05% at this point in time. In 2013, the Koruna-Euro exchange rate reached its upper limit set by the Czech National Bank. Euro area shadow short-term rates are therefore an eligible alternative.
The start of our sample is restricted by data availability. For the US and Canada, our samples start in 1990 because this marks the starting point of the VIX. For the four remaining countries, the OECD data set is the limiting factor, such that 1993 (1995) marks the beginning of the sample for Sweden (South Korea, the Czech Republic, and Hungary). Furthermore, by 1995, the Czech Republic and Hungary had already undertaken major transformations after the dissolution of the Soviet Union. Our sample ends with the last observation available in the SWIID 6.0 database, i.e. in 2014 for Korea, Sweden, and the Czech Republic and in 2015 for the US, Canada, and Hungary.

4.2.2 Methodology

With the described variables at hand, we estimate the following reduced-form VARX(P)-model:

$$Y_t = C + A_p(L)Y_{t-p} + \Gamma_q(L)X_{t-q} + \varepsilon_t\,. \tag{4.1}$$

$A_p(L)$ and $\Gamma_q(L)$ are lag-polynomial matrices of order p and q in the lag-operator L, where $p = 1, \ldots, P$ and $q = 0, \ldots, P$. C captures deterministic components (i.e an included constant) and ε_t is a column vector of reduced-form white noise error-terms and covariance matrix Σ_ϵ. X captures exogenous variables (i.e. the VIX for

[9]In fact, in Hungary and South Korea the short-term interest rate remains above 1% throughout the entire time considered. In Sweden, the short term interest rate is 0.5 from Q3 2009 to Q2 2010 and from Q3 2014. However, due to the quick recovery in 2010 and the small number of periods where the ZLB might have been binding, we restrain from the incorporation of a shadow rate.
[10]We want to thank the authors for data provision.

all non-US models). The lag-length P is determined by Akaike criterion.[11]
Identification of our underlying, unknown structural model of the form

$$B_0 Y_t = D + B_p(L) Y_{t-p} + \Theta_q(L) X_{t-q} + u_t, \tag{4.2}$$

and the respective shocks linked to it is conducted via sign restrictions. This requires a priori assumptions about the specific relations between the variables included in the VAR model. These assumptions can root in theoretical considerations as well as in empirically robust common wisdom.[12]
As we are interested in the interpretation of the effects of monetary policy shocks in a sensible manner, we only focus on the identification of the monetary policy shock and ignore other structural innovations to the model. Table (4.1) shows the assumed restriction scheme.

Variable	Gini	GDP	Prices	Interest Rate	REER
Imposed restriction	unrestricted	+	+	-	-

Table 4.1: Sign restrictions for an expansionary monetary policy shock.
Notes: Gini is a surrogate for all inequality measures and variables related to the factor income that are considered in this paper. The VIX is unrestricted in the US model. Imposed restrictions hold for four periods, but the results are not very sensitive to shorter durations.

We justify these assumptions as follows:
Expansionary monetary policy lowers overall market interest rates, either via policy rate cuts or monetary base expansion. This results in a stimulus of overall demand or at least does not cause demand to fall simultaneously. Overall prices should also adjust due to excess demand, or at least cannot be expected to decrease. The real exchange rate reaction is assumed to be negative because of capital outflows caused by overall lower yields in the economy. To capture the research question of this paper and pick up the controversy outlined in the discussed literature we leave the variables related to income inequality unrestricted. All restrictions are theory-implied and also confirmed in many empirical applications. We think that identification via sign restrictions is appropriate because we use fast-reacting financial markets variables as well as sticky variables such as the GDP or prices and thus do not want to restrict contemporaneous relations between the variables via e.g. an assumed ordering.

[11]The information criterion suggests a VAR(1)-model for the United States, Sweden, Czech Republic, and Hungary, a VAR(2)-model for Canada and a VAR(3)-model for South Korea.
[12]A detailed description of the idea and methodology can be found in Uhlig [27].

4.3 Monetary Policy and Income Inequality

The ultimate goal of this paper is a) to examine the nexus between income inequality and monetary policy, b) emphasize the role of redistribution, and c) trace the channels of transmission. By usage of the aforementioned restrictions, we can pursue this goal.

To examine the linkage between monetary policy and income inequality as well as the role of governmental redistribution, we distinguish between the Gini of gross income and net income. Thus, we can scrutinize the respective responses to monetary policy shocks. Since the discrepancy of gross and net incomes stems from paid and received (income-) taxes and transfers, we are thus able to tackle the question concerning the role of governmental redistribution.

4.3.1 Response of Gross Income Inequality

First, we evaluate the effect of expansionary monetary policy on the distribution of gross income.[13] Figure (4.3) depicts the responses of Gini gross to an expansionary 25bp monetary policy shock.

Two findings stand out. Inequality increases in all countries. The effect is most pronounced for the US, given a peak median response of 0.1 pp after 12 quarters (solid line), followed by Hungary. For the remaining countries, the peak response of the Gini index is above 0.015 pp.

Besides South Korea, the effect comes with some delay. It takes between eight and 30 quarters until the probability bands surpass the zero line. This finding comes at no surprise since the Gini index itself is rather sticky. Accordingly, the effect seems to be persistent since it seldom dies out after 40 quarters.

4.3.2 Response of Net Income Inequality

Focusing on net income Gini coefficients brings several advantages. First, the general debate about equitable income distribution is predominantly based on net values, such that potential dampening effects through governmental redistribution are incorporated. Furthermore, wealth is largely accumulated by savings that stem from the remaining share of income. Thus, a steady increase in income inequality might embrace an accelerating effect: low-income households are barely able to save and thus cannot accumulate wealth while, at the same time, high-income households amass

[13]For the sake of greater clarity, we only depict the responses of the Gini indexes. Since we use sign restrictions, the fundamentals react as intended. Nevertheless, the complete set of impulse responses is available upon request.

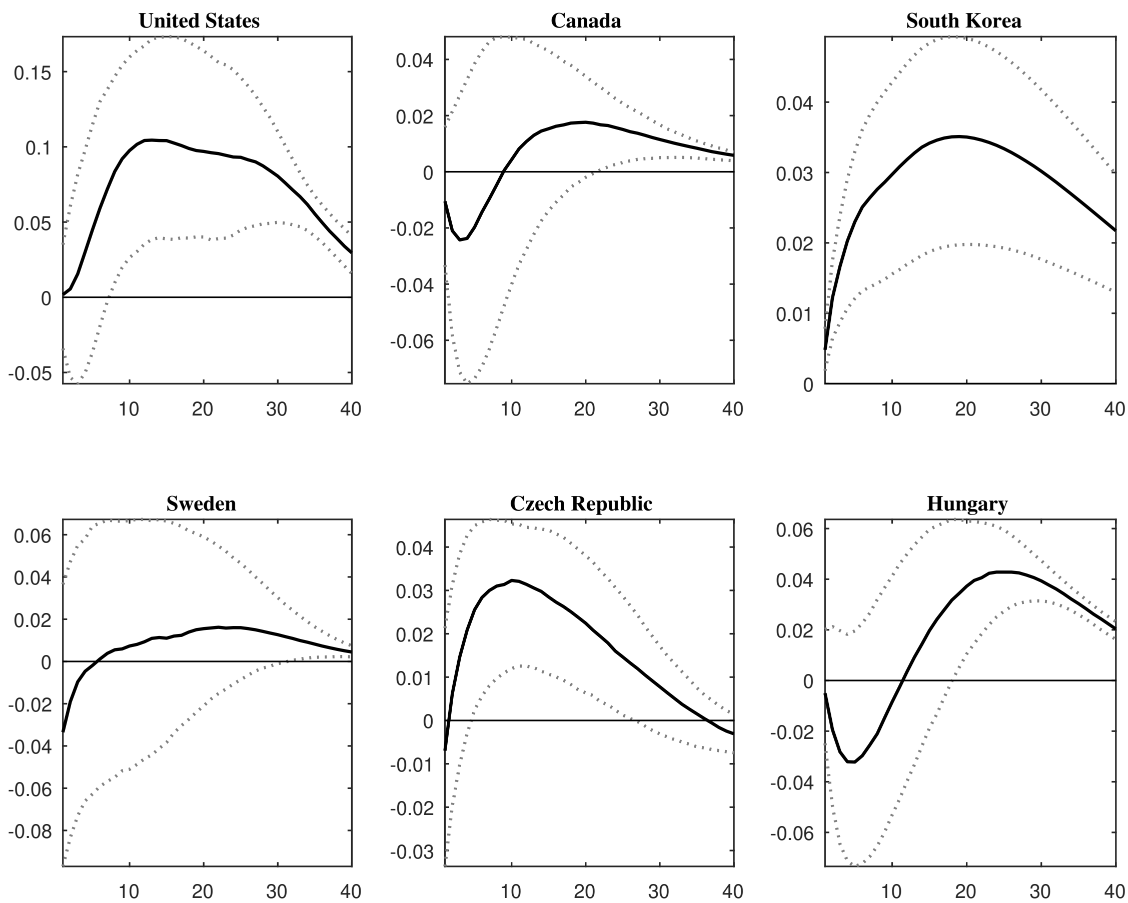

Figure 4.3: Response of Gini Gross.

Notes: Impulse responses of Gini gross to an 25bp expansionary monetary shock. The solid line depicts the median response. The dotted lines are the 16^{th} and 84^{th} percentiles.

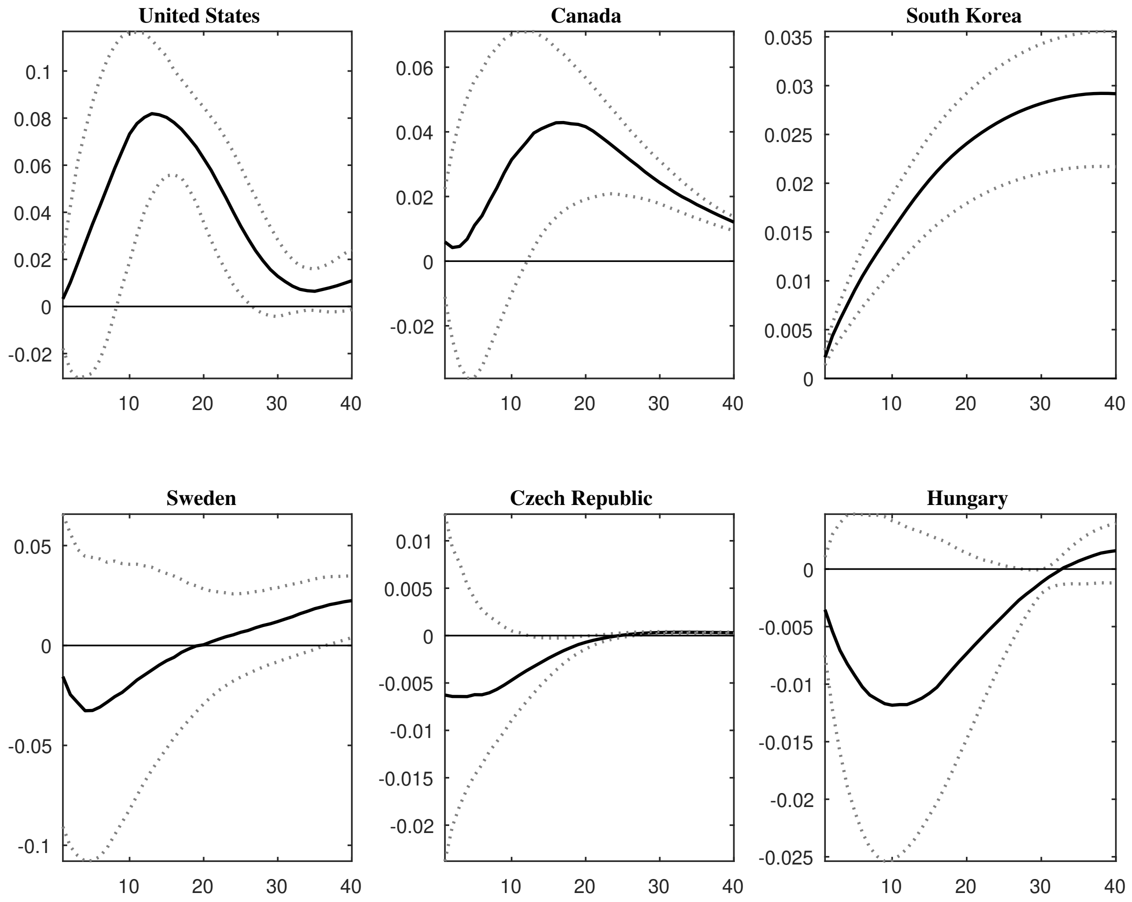

Figure 4.4: Response of Gini Net.

Notes: Impulse responses of Gini net to an 25bp expansionary monetary shock. The solid line depicts the median response. The dotted lines are the 16^{th} and 84^{th} percentiles.

wealth progressively, which in turn might increase inequality furthermore. Hence, monetary policy actions that benefit the latter disproportionately might even expedite this process. However, ultra-loose monetary policy as well as unconventional monetary policy measures are under suspicion to be such policy actions. In this respect, Montecino and Epstein [17], Mumtaz and Theophilopoulou [19], and Saiki and Frost [25] find a positive relation between unconventional monetary policy and inequality hikes for the US, UK, and Japan, respectively. As their analysis excludes top-income households or ends before the introduction of unconventional measures, these papers might even underestimate the unveiled effects.

Figure (4.4) outlines the results of our baseline model including the Gini of net income as our measure of inequality. It stands out that the effect of an expansionary shock is mostly tempered, compared to the response of Gini gross in figure (4.3). For the US, we find a positive reaction in the short-term perspective that is notably smaller, namely 0.08 pp at its peak, than the rigid increase in Gini gross with its maximum at 0.1 pp. The difference between Gini gross and Gini net is most pronounced in Sweden, the Czech Republic, and Hungary - the countries with the highest relative redistribution in our sample. Here, the tendency for an increase in inequality is immensely mitigated. Finally, we find no notable difference in the response of the Gini net in Canada as against the response of Gini gross.

In summary, we find that governmental redistribution can dampen the effect of expansionary monetary policy on income inequality. Furthermore, it seems that the extent of redistribution matters more than the initial level of inequality. Sweden, the Czech Republic, as well as Hungary - countries with the highest relative redistribution in our sample - experience the strongest dampening effect. South Korea, that has low levels of income inequality combined with low levels of redistribution, faces similar effects as the US and Canada.

Our findings are in line with Saiki and Frost [25], Montecino and Epstein [17], and Mumtaz and Theophilopoulou [19], but contrast the much-noticed work by Coibion et al. [8]. The discrepancies in the findings are likely linked to the following issues: Firstly, our Gini measures differ. Coibion et al. [8] derive their Gini measures from household survey data that do not cover the top 1% of the income distribution. This is troublesome given the dominant role of top income households among the income distribution, as emphasized by Atkinson et al. [5]. For example, in 2007 the top 1% accounts for about 23% of the total received income in the US. Therefore, we rely on the mean estimator from the SWIID which incorporates the complete income distribution. Another merit of this database is that it enables cross-country comparability. Secondly, the debate about increasing income inequality gained momentum especially since the Financial Crisis and the associated conduct of monetary policy. We take this extraordinary period into account. Lastly, we apply a substantially different estimation approach.

4.4 Transmission of Monetary Policy on Inequality

In this section, we want to elaborate what channel-related variables are involved in the transmission of monetary impulses to overall income dispersion. As outlined above, we focus on the employment channel and the income composition channel. We pick up the ideas of Bernanke and Gertler [7] who disentangle overall transmission of monetary policy shocks to the real economy by taking a closer look at variables assumed to be involved in the transmission. With this approach, they shed light on major driving forces and related channels of monetary transmission linked to them. Similarly, we use variables related to the channels outlined previously to account for the variety of possible mechanisms that drive the observed movement in the overall Gini coefficients presented in chapter (4.3). These variables replace our Gini coefficient in the baseline VAR model while identification assumptions remain unchanged. We proceed as follows: First, we examine in how far the employment channel is involved in the transmission of monetary policy. Second, we separately include both components of the income composition channel in our VAR model. Third, we relate them to each other to figure out in how far their ratio is affected by monetary policy, or, in other words: Does the reaction of one income component dominate the reaction of the other. Thus, we need variables that can be assigned to the channels to assess the importance and overall role each channel plays in the six countries. We describe them in the following in more detail.

4.4.1 Employment Channel

Data

To take a closer look at the employment channel, we check in how far employment reacts to monetary policy shocks. In contrast to most literature, we do not use unemployment rates, but overall employment instead because the officially reported rates are often biased since not every unemployed person registers. Additionally, changes in the labor force participation might distort unemployment rates although overall employment remains less affected or even unchanged. Thus, our measure captures more precisely the real utilization of the factor labor in our samples. To have a common data source, we rely on total employment provided by the OECD.[14]

Results

According to the employment channel, an expansionary monetary policy shock lowers income inequality via its stimulating effect on the labor market. Typically low-skilled low-income households benefit from this channel. To evaluate the relevance of this channel, we substitute the Gini variable with the log of total employment in the respective country.

Figure (4.5) shows the impulse responses of employment to an expansionary monetary policy shock. Such shocks have a notable stimulating impact on employment in all countries. The reaction in employment is in general weaker in the countries

[14] Due to data issues for the US we proxy the total number of employed persons by the employed workers according to the non-farm payroll statistics.

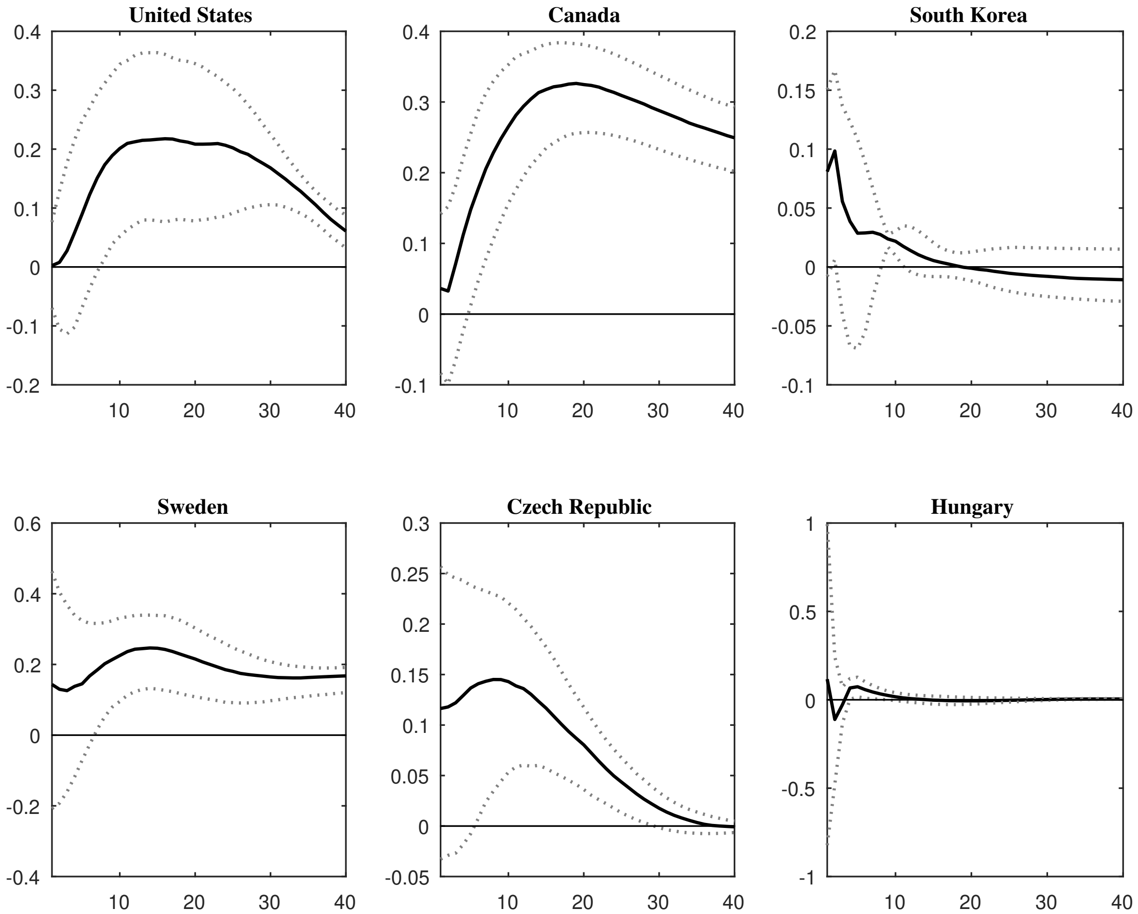

Figure 4.5: Monetary Policy Shocks and Employment.

Notes: Impulse responses of employment to an 25bp expansionary monetary policy shock. The solid line reflects the median response, the dotted lines show the 16^{th} and 84^{th} percentiles.

with high redistribution. This can probably be linked to their more regulated labor markets, e.g. higher degrees of dismissal protections.

The contrasting responses of the Gini net on the one hand and employment on the other hand indicate that the employment channel is dominated by other driving forces. Hence, we take a more detailed look at the primary factor income sources of households: labor and capital.

4.4.2 Income Composition Channel

Data

The income composition channel distinguishes between major sources of households' overall earnings: labor-related income and capital pay-offs. Thus, we include these different sources into our analysis. As we are primarily interested in net effects, we focus on disposable income. National accounts and income statistics provide detailed data to construct different variables based on the sub-components related to the production factors capital and labor. More precisely, in our analysis capital income consists of net interest income, dividends after taxes and net rental income. It is computed as the sum of net operating surplus, which is gross operating surplus (GOS) less consumption of fixed capital for the corporate sector, and net mixed income (NOS+NMI). Labor income incorporates solely (net) compensation of employees, i.e. wages, salaries, and employers' social contributions.[15] Again, we rely on data from the OECD to overcome possible problems of cross-country comparability.[16]

For South Korea, all income data are only available on a yearly frequency. Thus, we need to interpolate capital- and labor-related income. For the Czech Republic, the net operating surplus and the mixed income is only available from 1999. Since gross operating surplus and mixed income (GOS+MI) is accessible from 1995, we construct NOS+NMI from 1995 to 1998 by assuming the share of NOS+NMI in GOS+NMI in this time is identical to the share in 1999.[17] For Hungary, the OECD provides quarterly data for labor-related income and GOS+NMI, but only yearly data for NOS+NMI. This time we first construct each quarters' share in the yearly values of GOS+NMI. We then assume that the share for NOS+MI is identical.

Response of Labor-Related Income

We replace the Gini variable in the baseline model by the log of labor-related income. Since labor income and employment are highly correlated, their outcomes are expected to be similar, too.

The results are represented in figure (4.6). In all countries, labor-related income increases after an expansionary shock. The peak median responses vary between about 1.1 pp (Sweden) and about 0.1 pp (South Korea).

Unfortunately, we cannot draw conclusions about the distribution of labor income across households. Nevertheless, wages are the primary income source for the vast majority of households. In combination with the findings we draw from the employment channel, the results on labor-related income indicate that employees benefit from an expansionary monetary policy shock.

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[15] Including transfers, for some households the dominant income source, would have been an option if all countries collect and process data on a similar approach and provide them for sufficiently long periods. Unfortunately, for the sake of cross-country comparability, we cannot include them in a meaningful manner.

[16] All data are seasonally adjusted and denoted in constant prices.

[17] The share of NOS+NMI in GOS+NMI varies between 55% and 62% from 1999 to 2014.

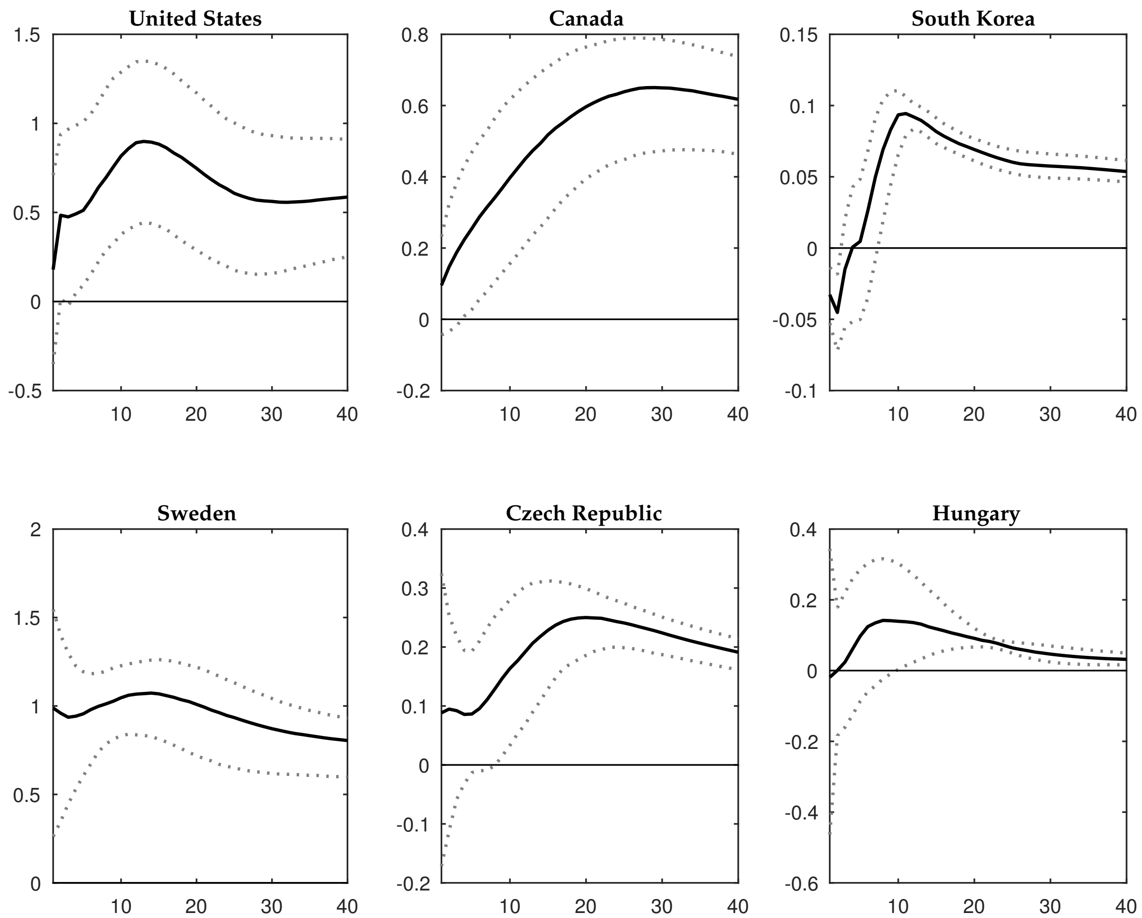

Figure 4.6: Monetary Policy and Labor Income.

Notes: Impulse responses of labor-related income to an 25bp expansionary monetary policy shock. The solid line reflects the median response, the dotted lines show the 16^{th} and 84^{th} percentiles.

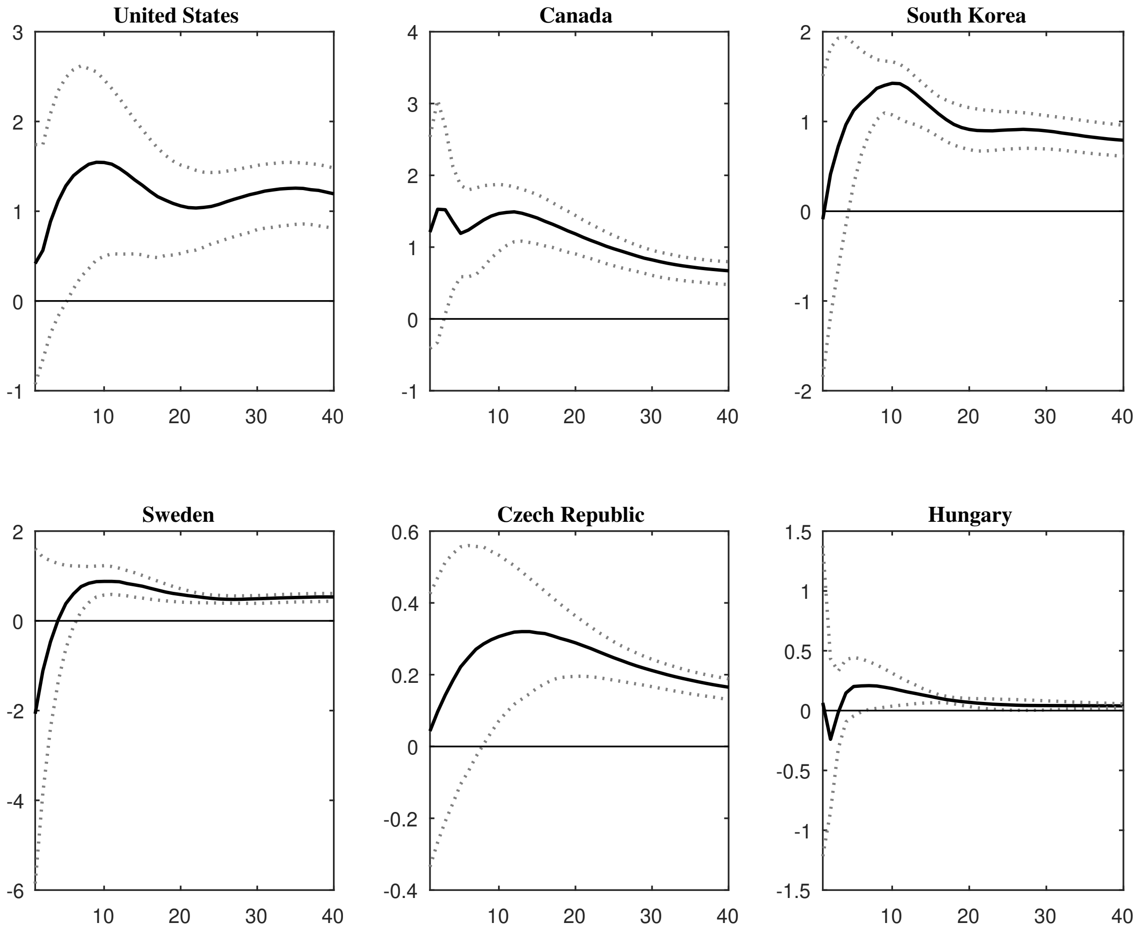

Figure 4.7: Monetary Policy and Capital Income.
Notes: Impulse responses of capital-related income to an 25bp expansionary monetary policy shock. The solid line reflects the median response, the dotted lines show the 16^{th} and 84^{th} percentiles.

Response of Capital Income

To obtain aggregate net capital income, we sum up net operating surplus and net mixed income. Following Atkinson et al. [5], we assume that high-income households are the main receiver of capital income. Thus, an increase in capital income indicates that these households benefit disproportionately, as opposed to low- and middle-income households.

Figure (4.7) indicates a similar pattern of net capital income to labor income. There is a notable increase in capital income in all countries. Besides the boost in asset prices, the stimulus of real activity leads to e.g. increasing corporate profits or rents and thus higher capital earnings for shareholders or real estate owners.

We find the most pronounced responses for countries with relative little redistribution, i.e. peak responses greater than one. While the size of the responses of the Czech Republic and Hungary are quite small, the impulse response of Sweden is similar to those of less redistributing countries.

Response of the Capital-Wage-Ratio

As has been shown above, an expansionary monetary policy shock leads to an increase in both, capital income and labor-related income. Depending on the composition of income among households, this leads to either a rise or a fall in inequality. The income composition channel states that income inequality growths if capital income receivers benefit disproportionately, and vice versa. Hence, we finally evaluate the relevance of the income composition channel via the response of the capital-wage-ratio after such a monetary policy shock. Since labor-related income also represents changes in employment, the capital-wage-ratio is not only suited for the evaluation of the income composition channel. It also indicates whether the income composition channel is dominating the employment channel.

The respective impulse responses are presented in figure (4.8). Out of the countries with relatively little redistribution, the US and Canada exhibit a clear increase in the capital-wage-ratio. In contrast, the responses of the extensively redistributing countries show either no clear response (Czech Republic and Hungary) or even a negative reaction (Sweden). South Korea stands out as a special case here. While capital owners benefit disproportionately in the short-term in South Korea, this effect is reversed after roughly 15 quarters.

How does monetary policy impact inequality? We find evidence that the primary mechanism is the composition of income. The increase in Gini cannot be explained by the employment channel because we expect that low-income households benefit from a stimulated labor market. Additionally, the labor market reacts stronger in less redistributing countries. The increase in the Gini net is in contrast to that finding. At the same time, we find that capital income increases more than labor income. Taken together, it is likely that the income composition channel explains the nexus between monetary policy and income inequality. This is true for both, much redistributing and less redistributing countries. Nevertheless, since the first-mentioned do not show an increase in net income inequality after expansionary monetary policy shocks and no increase in the capital-wage-ratio, both types of net factor income benefit more equally from expansionary monetary policy shocks in these countries. Thus, we conclude that income composition plays the primary role in the transmission of monetary policy shocks on income inequality.

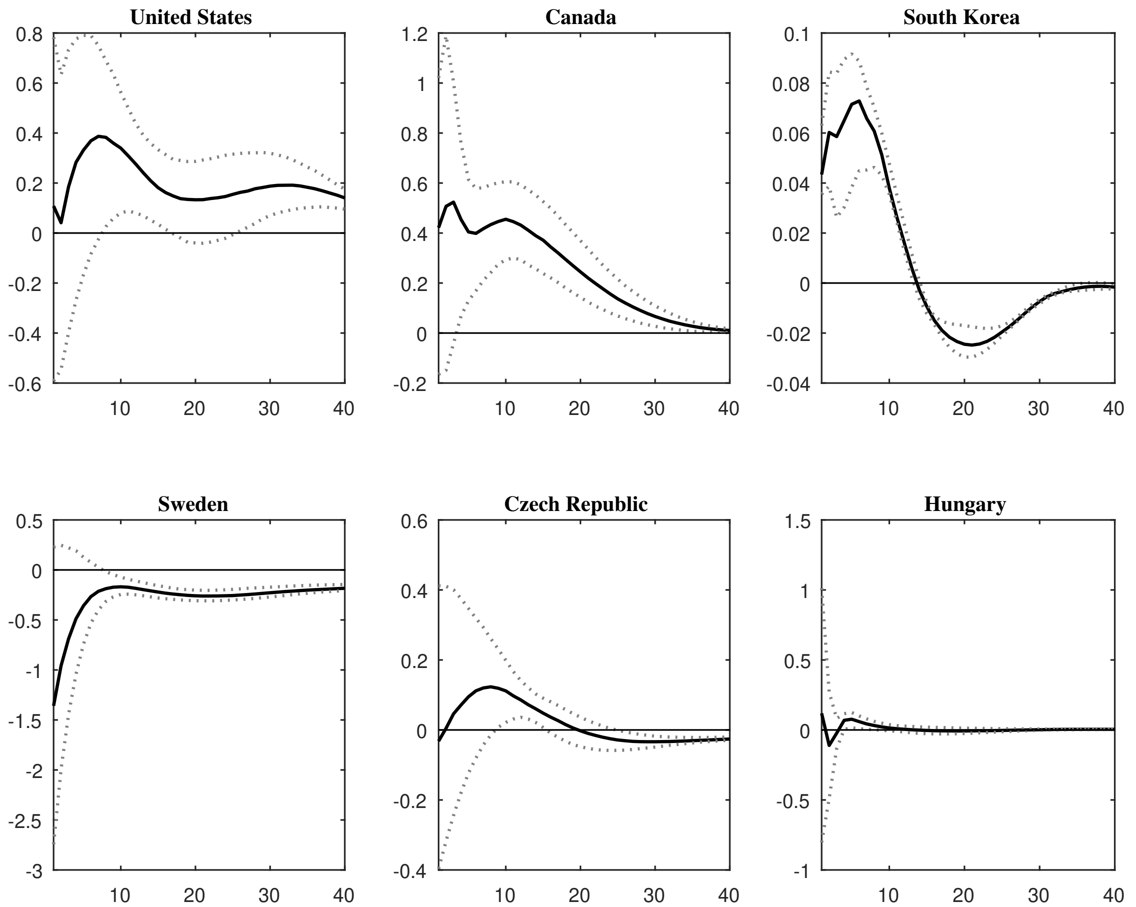

Figure 4.8: Monetary Policy and the Capital-Wage-Ratio.

Notes: Impulse responses of the capital-wage-ratio to an 25bp expansionary monetary policy shock. The solid line reflects the median response, the dotted lines show the 16^{th} and 84^{th} percentiles.

4.5 Robustness

In this section we asses whether the results hold under different model specifications. One major concern about the methodology applied above is about the use of interpolated data. We verify whether our results hold if we incorporate yearly data instead. Furthermore, we follow Coibion et al. [8] and present evidence that uses local projections as additional robustness. Finally, we check the sensitivity of our results to various samples.

4.5.1 Yearly VAR Model

The results found above rely on the assumption that the quarterly data we receive from linear interpolation of the Gini coefficients are similar to the true but unknown quarterly Gini coefficients. Thus, we test the outcome of our model by applying a VAR model with yearly data. If the results of the yearly and the quarterly VAR model are similar, we are confident that linear interpolation does not substantially affect the estimates. With the resulting shorter sample size we now incorporate only one lag and reduce our restriction duration to one period as well. Nevertheless, the short sample boosts uncertainty in the estimation and thus the resulting percentiles of the presented model should be treated with caution. Despite that, the major outcomes remain unchanged.

We again start by showing impulse responses of Gini gross (see figure (4.9)). In line with the findings from section (4.3) there is a tendency of an increase in inequality after an expansionary monetary policy shock in five of the six countries. Only Canada shows no clear pattern.

The impact of expansionary monetary policy shocks on the Gini net, figure (4.10), is again quite heterogeneous across countries. In economies characterized by a high degree of redistribution, we can observe lower sensitivity to a shock. In contrast, countries with little governmental interaction show no or, for the US, a positive reaction. The mitigating effects of governmental interventions can hence be supported by these outcomes.

4.5.2 Local Projections

Thus far, we have solely considered VAR models. We now follow Coibion et al. [8] and assess the role of monetary policy shocks for income distributions via impulse responses from local projections, as suggested by Jordà [13]. This methodology describes the response of an endogenous variable (i.e. Gini coefficient) to a monetary policy shock that enters as an exogenous variable into the model. The choice of the

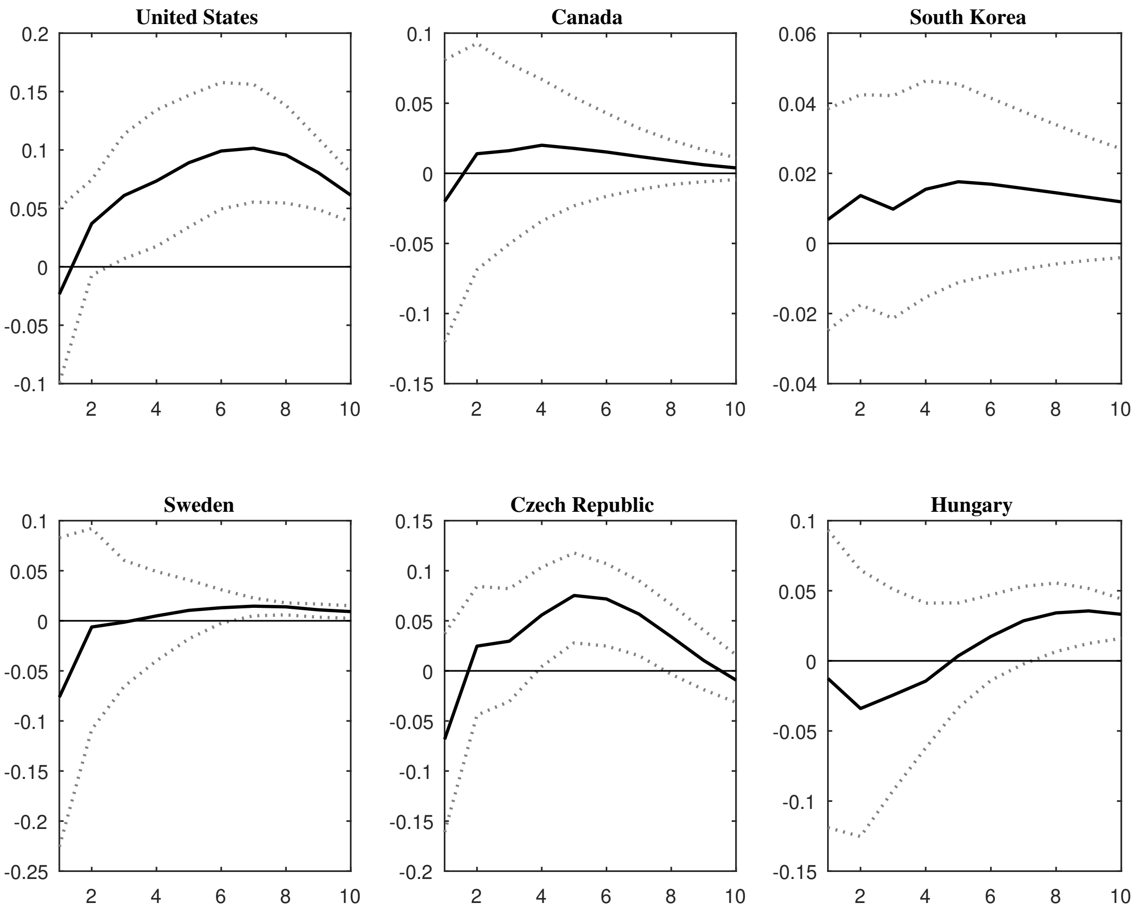

Figure 4.9: Monetary Policy and Gini gross, yearly model.

Notes: Impulse responses of Gini gross to an expansionary monetary policy shock. Estimates with yearly data. The solid lines reflect the median responses, the dotted lines are the 16^{th} and 84^{th} percentiles.

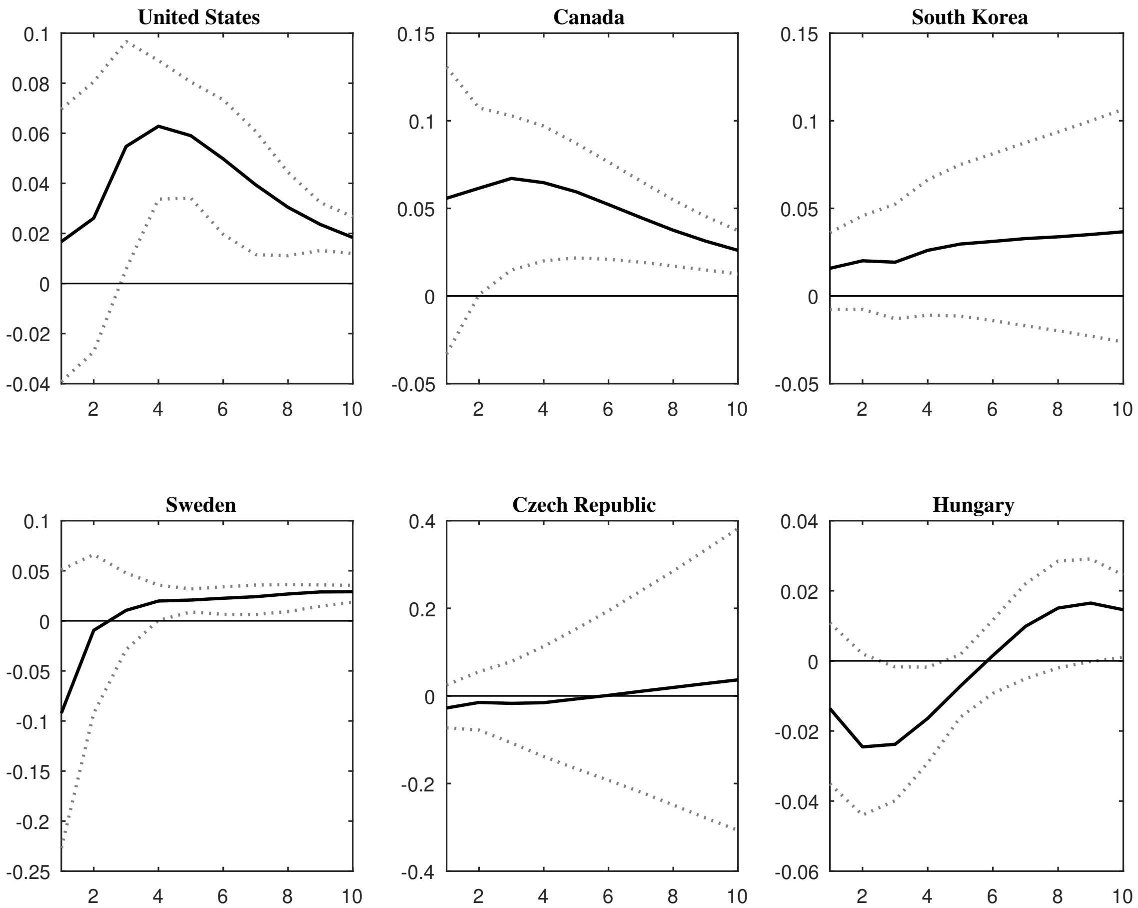

Figure 4.10: Monetary Policy and Gini net, yearly model.

Notes: Impulse responses of Gini net to an expansionary monetary policy shock. Estimates with yearly data. The solid lines reflect the median responses, the dotted lines are the 16^{th} and 84^{th} percentiles.

incorporated exogenous shock deserves further attention. Coibion et al. [8] use Romer and Romer [24] shocks for this purpose. This approach suites not well to our specific data set for two reasons. First, Romer and Romer [24] shocks are only available up to the point where short-term interest rates hit the ZLB. We explicitly want to account for periods characterized by unconventional monetary policy. Second, as Romer and Romer [24] shocks are only available for the US, our analysis would lose its cross-country dimension. Thus, we derive our exogenous quarterly monetary policy shock for each country from a standard three variable VAR model consisting of real GDP, consumer prices, and key policy rates, identified via recursive ordering which relies on the assumption that monetary policy reacts contemporaneously to output and prices, but not vice versa.[18]

With these exogenous shocks at hand, we estimate local projections. Following Jordà [13] our model is given by

$$y_{t+h} = c + \beta_h \hat{u}_t^{MP} + \gamma_h' \sum_{s=1}^{q} y_{t-s} + \varepsilon_{t+h} \,. \tag{4.3}$$

Hereby, y_t is the inequality measure and $\hat{u}_t^{MP}$ the policy shock that stems from the VAR model described above. We set $q = 4$ so that the four latest inequality measures that appeared before the shock are incorporated as control variables.[19] By plotting β_h as a function of h along with error bands we get impulse responses. To circumvent serial correlation among the residuals, we apply Newey-West standard error correction. The resulting impulse responses are depicted in figure (4.11) and (4.12).

In line with our VAR findings, we observe in four out of six countries a clear increase in the Gini gross after an expansionary monetary policy shock. South Korea and the Czech Republic display an increase in at least some periods.

Regarding the Gini net, local projections confirm our previously presented results as well. Countries with a high degree of redistribution show no clear pattern. This indicates that governmental intervention is able to dampen the effect of monetary policy shocks on gross income dispersion.

It is worth noting that despite the use of a similar methodology as Coibion et al. [8] we obtain diverging results. Hence, we next test whether the differences stem from different samples.

[18]The correlation between the resulting shock series (for the US economy) and the quarterly aggregated Romer and Romer [24] shocks is about 0.6 for the available period (1990 to 2007).

[19]Altering q does not yield substantially different results.

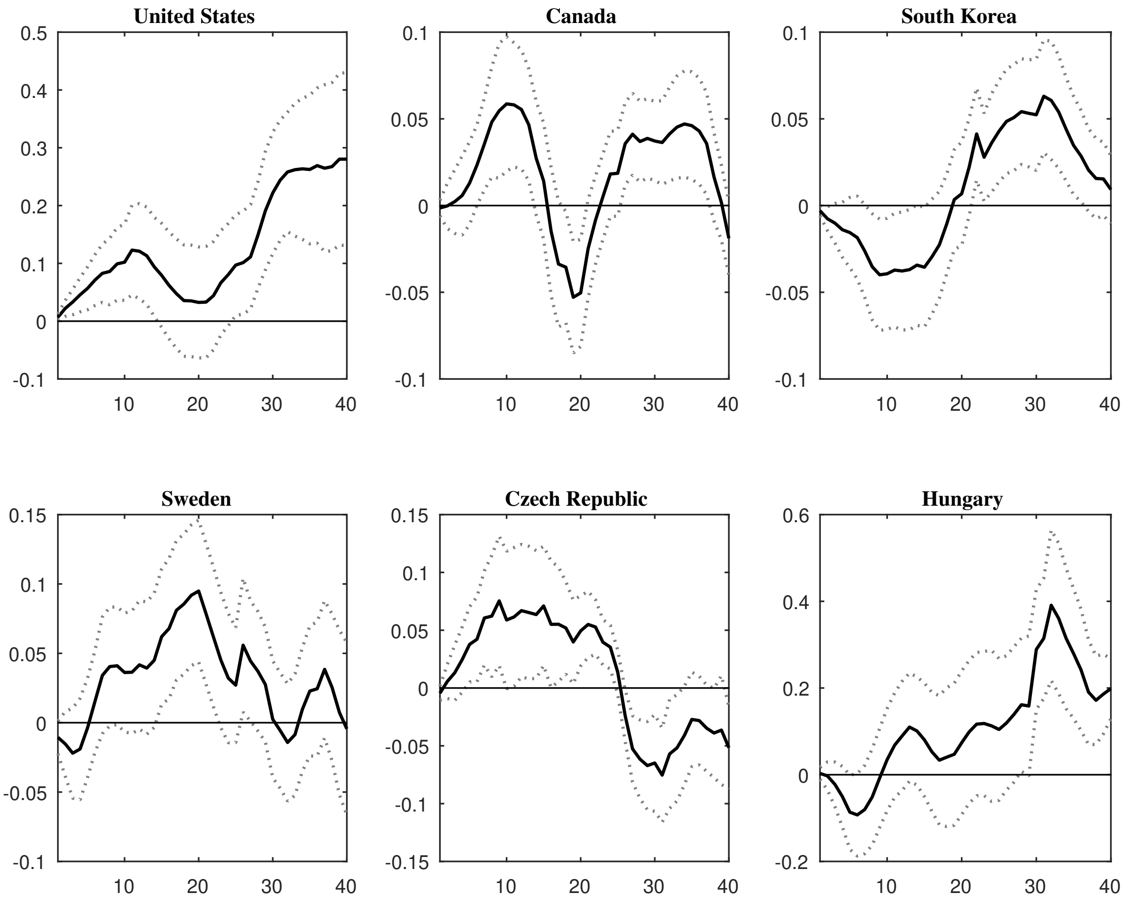

Figure 4.11: Local Projections for Gini Gross.

Notes: Local projections for β_h (solid line) and the respective one standard error bands (dotted lines). Shock measured in standard deviation units and inverted to reflect expansionary shocks.

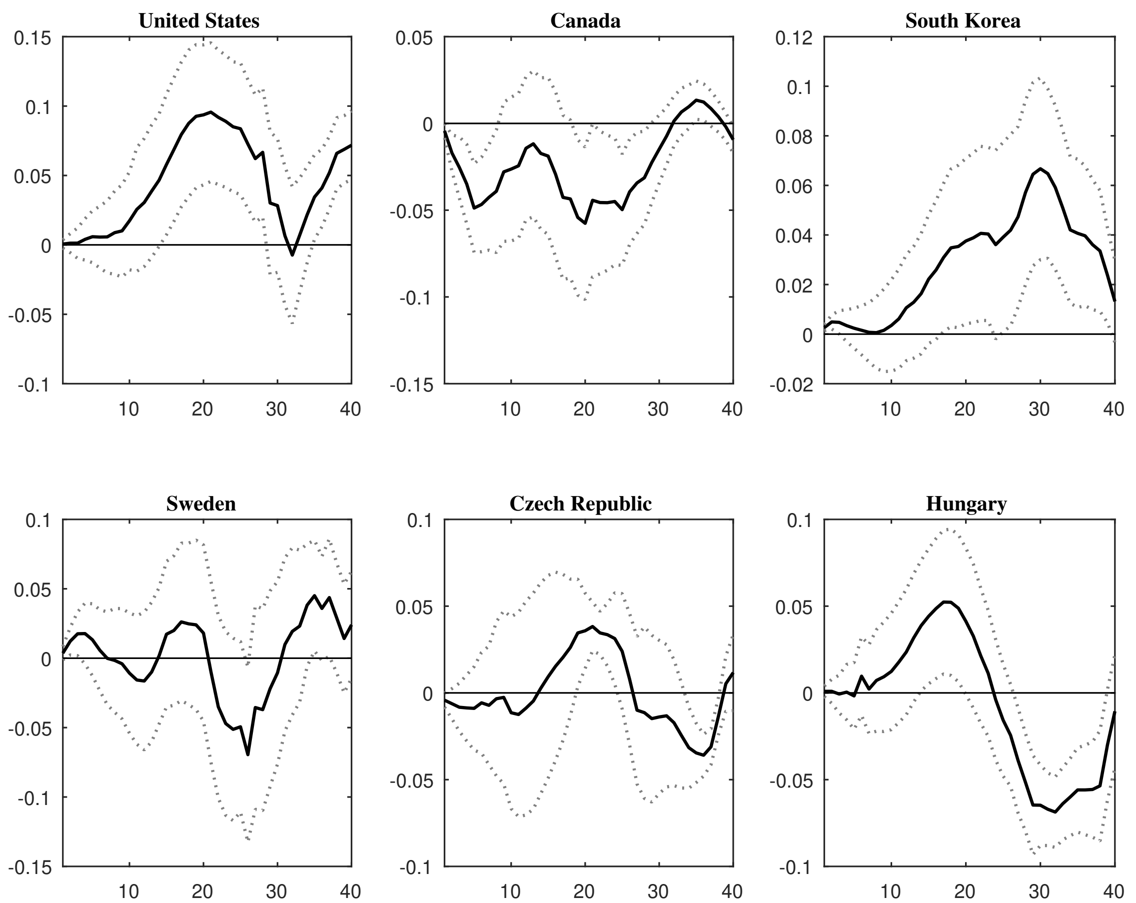

Figure 4.12: Local Projections for Gini Net.

Notes: Local projections for β_h (solid line) and the respective one standard error bands (dotted lines). Shock measured in standard deviation units and inverted to reflect expansionary shocks.

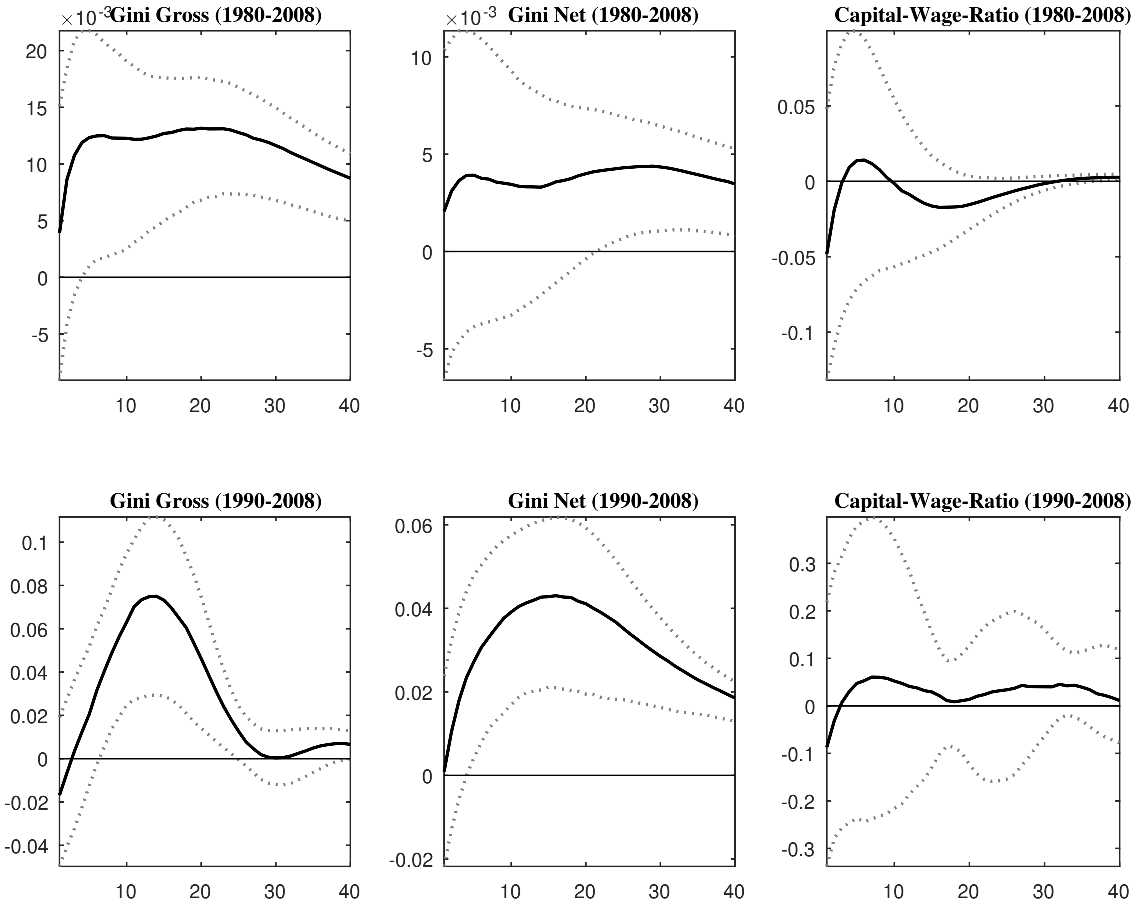

Figure 4.13: US: Excluding Financial Crisis.
Notes: Impulse responses of net Gini to an expansionary monetary policy shock. The solid lines reflect the median responses, the dotted lines are the 16^{th} and 84^{th} percentiles. VIX exluded in sample 1980-2008 (upper row) and included in sample 1990-2008 (er row).

4.5.3 Sample Size

Thus far, data availability limited the analyzed estimation horizon from the beginning of the 1990s to 2014 or 2015, respectively. To ensure the comparability with Coibion et al. [8] we perform two further robustness exercises: we firstly estimate a US model akin Coibion et al. [8] before we incorporate the recent financial crisis to examine its effect on the nexus between monetary policy shocks and income inequality.

One discussed driving force for the nexus between income inequality and expansionary monetary policy are the unconventional monetary policy measures following the Financial Crisis.

Figure (4.13) presents model outcomes for 1980 Q1/1990 Q1 - 2008 Q4. The results do not differ notably from our results so far, no matter whether we estimate a model with or without the VIX (1990 Q1 vs. 1980 Q1).

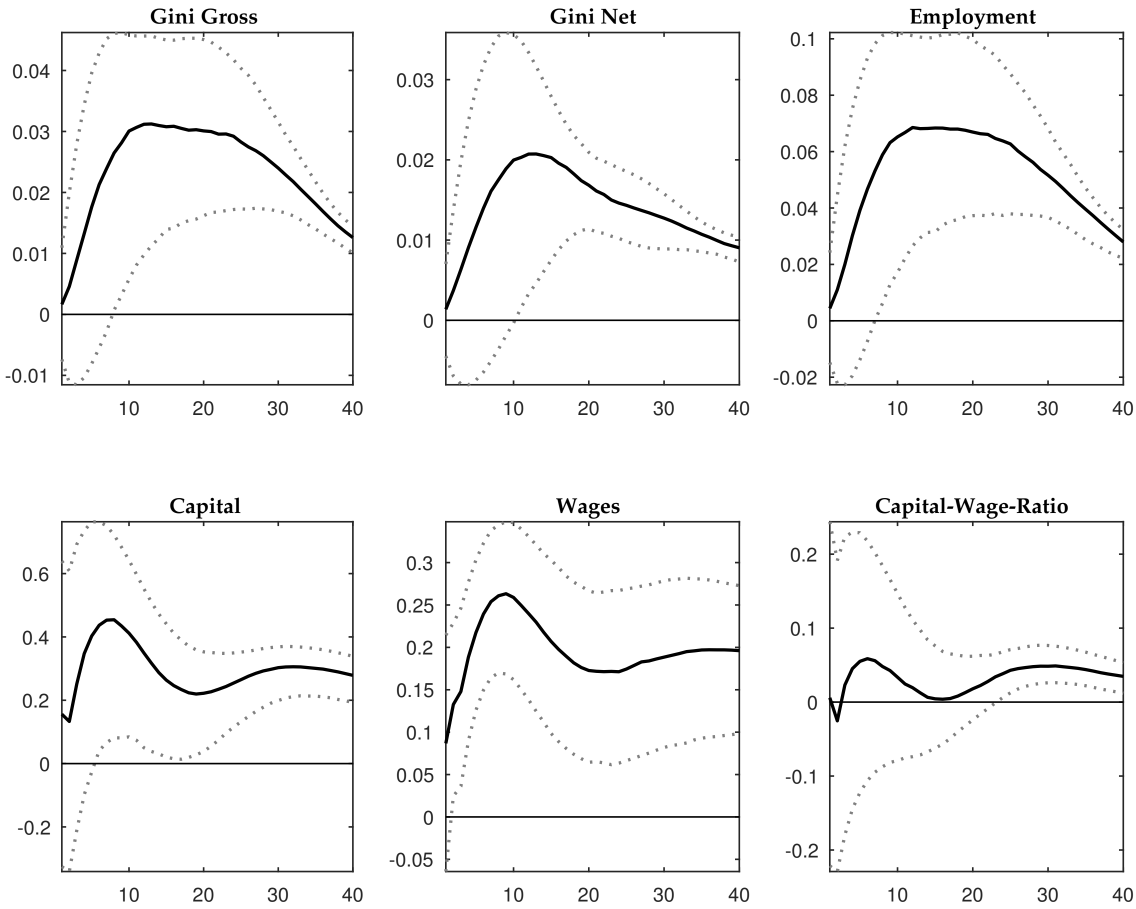

Figure 4.14: US: Long Sample 1980 - 2014.
Notes: Impulse responses of net Gini to an expansionary monetary policy shock. The solid lines reflect the median responses, the dotted lines are the 16^{th} and 84^{th} percentiles.

If we include the recent Financial Crisis into our sample, the magnitude of the response of inequality to a monetary policy shock increases, see figure (4.14). As pointed out by Montecino and Epstein [17], unconventional monetary policy measures have indeed hiked income inequality in the US. Our analysis supports their findings.
In brief, our results are qualitatively robust to a variety of methodological as well as sample selection aspects. Expansionary monetary policy shocks increase income inequality.

4.6 Conclusion

In the recent decade, the issue of rising income inequality gained more and more attention in the public perception as well as in the political debate. The nowadays observable historically high levels of income dispersion are accompanied by an environment of very expansionary monetary policy. In this respect, we add new empirical evidence to the current controversy. To assess the effects of monetary policy shocks, we incorporate Gini coefficients in a standard macroeconomic VAR model consisting of GDP, consumer prices, a monetary policy variable, and the corresponding real exchange rate. Gini coefficients of gross incomes increase in all countries, namely the US, Canada, South Korea, Sweden, the Czech Republic, and Hungary, when facing expansionary monetary policy shocks. In contrast, the reaction of net income dispersion varies between the countries under consideration. Countries with a relatively low degree of redistribution, i.e. the US, Canada, and South Korea, show notable positive reactions of Gini net in the presence of expansionary monetary policy shocks. On the contrary, this measure does not increase in countries with a high degree of redistribution.

Furthermore, we take a more detailed look at the importance of two major transmission channels, the employment channel and the income composition channel. The reaction of employment, captured by the total number of employed people, shows the expected positive sign in all countries. Again, the reaction is weaker and less pronounced in countries with a high degree of redistribution. By splitting the composition of net national income into its major parts, labor-related income and capital-related income, we can evaluate which income category benefits disproportionately. While both components are in general affected positively, their ratio indicates that in the US, Canada, and South Korea capital owners benefit disproportionately. As the increase in employment can not offset the surge in net income inequality we conclude that the composition of income outweighs the positive labor market effects. The capital-wage-ratio indicates that in countries with a high degree of redistribution both income sources seem to profit similarly. We conclude that the distributional effects of monetary policy (on disposable income) can be addressed by the degree of governmental intervention.

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5 Concluding Remarks

Since the outstanding crises in recent years, central banks moved into the focus not only of professionals but also of the broad public. This shift in attention is primarily driven by both the extra-ordinary nature of policy measures as well as by concerns about the effects of monetary policy. While most Western central banks have quite narrow objectives, maintaining price stability and balance real activity around its long-run-equilibrium, the impact of their policies is very vast, as they affect economic activity and financial markets via a broad spectrum of channels. Within this doctoral thesis, four paper pick up distinct aspects and effects of monetary policy that go beyond the narrow view of evaluating central bank policies by means of their primary objectives.

The first paper deals with the role the Fed plays within US household debt, especially mortgage debt. We show that the nexus between monetary policy and household debt is time-varying and that structural characteristics like the share of adjustable-rate-mortgages seem to be a candidate driver of this time-variation. Furthermore, we show that the task of deleveraging of households should not be directed towards a restrictive monetary policy, as it is relatively costly, in terms of employment. Thus, this paper contributes to answering the quite complicated question about the role central banks play and should play within the built-up of high levels of private sector debt, but also within a potential deleveraging.

Paper two and three lay their focus on the effects of monetary policy on risks inherent in the financial system. Both papers pick up very actual problems and potentially harmful side effects of the currently prevailing monetary policy environment, as both banks and asset markets are challenged by low-for-long yields. Hence, these two papers aim at fostering the soundness of European banks and asset markets. An alternative perspective to unveil the amplifying nature of monetary policy transmission via the financial system through risk-taking in the European banking sector is introduced by paper two. It emphasizes that disproportionately strong adjustments in credit standards of banks in response to, for example, a policy loosening, bear the caveat that European banks engage in an inadequate manner within their core business, implicating possible balance-sheet risks. Paper three sheds light on the asymmetric reaction of different assets to monetary policy shocks, conditional on distinct risk regimes. Besides state-dependency of the asset reactions, we find that the susceptibility of different assets to monetary policy shocks highly depends on the respective risk-regime. Consequently, investors and policy makers have to take the prevailing risk environment into account when assessing the unveiled asymmetric impact of changes in short-rates.

The fourth paper deals with monetary policy's effects from a socio-economical perspective, as it focuses on its distributional consequences. We show that income stemming from capital benefits disproportionately from loose monetary policy. The mitigating effect of a relatively high degree of redistribution indicates that these effects can successfully be tackled by the respective design of national tax and social politics.

All the papers pick up with very actual research questions and have quite strong implications for central bankers, but also for politics. They show that maladjustment and undesirable developments go hand in hand with monetary policy. These problems have to be addressed, as they are of particular interest to maintain a stable economic, financial, and social environment. While this doctoral thesis can neither recommend a primary recipient nor a panacea for these problem sets, it helps to quantify the effects monetary policy has on them.

6 Affidavit

Ich erkläre hiermit, dass ich die vorgelegten und nachfolgend aufgelisteten Aufsätze selbstständig und nur mit den Hilfen angefertigt habe, die im jeweiligen Aufsatz angegeben sind. In der Zusammenarbeit mit den angeführten Koautoren war ich mindestens anteilig beteiligt. Bei den von mir durchgeführten und in den Aufsätzen erwähnten Untersuchungen habe ich die Grundsätze guter wissenschaftlicher Praxis, wie sie in der Satzung der Justus-Liebig-Universität Gießen zur Sicherung guter wissenschaftlicher Praxis niedergelegt sind, eingehalten.

Jörg Holger Schmidt, Gießen, den 06. Januar 2020

I hereby declare that I completed the papers submitted and listed hereafter independently and only with those forms of support mentioned in the relevant paper. When working with the authors listed, I contributed no less than a proportionate share of the work. In the analyses that I have conducted and to which I refer in the papers, I have followed the principles of good academic practice, as stated in the Statute of Justus-Liebig-University Gießen for ensuring good scientific practice.

Jörg Holger Schmidt, Gießen, January 06 2020

Submitted Papers:

I. Schmidt, J. [2020]: 'Risk, Asset Pricing and Monetary Policy Transmission in Europe: Evidence from a Threshold-VAR Approach', *Journal of International Money and Finance* (forthcoming).
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II. Finck, D., Schmidt, J. and Tillmann, P. [2018]: 'Mortgage Debt and Time-Varying Monetary Policy Transmission', *MAGKS Joint Discussion Paper Series in Economics*, 09-2018.
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