International dynamics of inflation expectations

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Abstract

To what extent are US and Euro Area (EA) inflation expectations determined by foreign shocks? How do transmissions change during the Great Recession and European sovereign debt crisis? We address these questions with a flexible structural VAR model of weekly financial markets' inflation expectations and an index of commodity futures. For the identification of the model, we exploit the heteroscedasticity of the data. We propose instrument-type regressions to uncover the economic nature and origin of identified shocks. In line with the discussion about global inflation, we find that inflation expectations can be labeled *global* over short expectations horizons but *local* at long horizons. While a large US macro shock explains the strong drop in US and EA inflation expectations in the beginning of the Great Recession, expectations shocks are the important driver during sustained crisis times.

Keywords: Spillover, monetary policy, expectations shocks, financial crisis, identification through heteroskedasticity, variace decomposition.
JEL classification: E31, F42, E52.

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1 Introduction

Private agents' expectations play a key role in modern monetary economics. In particular, inflation expectations have become a widely recognized variable, whose successful control is well-known to facilitate greater stability of output, employment and prices. For that reason, central banks like the Federal Reserve Bank (FED) and the European Central Bank (ECB) commit to anchored inflation expectations. Recently, the FED and ECB determined inflation expectations as an important variable of their forward guidance strategies.[1] Yet in spite of their prominent role, the nature of inflation expectations and its transmission channels are not fully understood.

While the literature on cross-country linkages of actual inflation rates is well developed and extensively discussed (recent important contributions include Ciccarelli and Mojon (2010), Mumtaz and Surico (2012), Wang and Wen (2007), Henriksen et al. (2013)), empirical evidence with regards to inflation expectations is significantly lagging behind. In a New Keynesian Phillips Curve context, knowledge about international linkages in expectations contributes to the understanding of dynamics in actual inflation rates. Ciccarelli and Mojon (2010) and Neely and Rapach (2011) find that the variance of US inflation rates is explained by up to 70% by a global factor. When it comes to inflation expectations, however, empirical studies focus on the anchoring (Gürkaynak et al. (2010b), Jochmann et al. (2010), Strohsal and Winkelmann (2015)) or structural drivers (Leduc et al. (2007), Mehra and Herrington (2008), Clark and Davig (2011)) in single country models, but are silent about international transmissions. Against this backdrop we ask: To what extent are inflation expectations determined by foreign shocks?

From both an empirical and theoretical perspective it is widely established that inflation expectations dynamics are governed by two distinct classes of shocks: standard macro and expectations shocks. Following the definitions of Leduc et al. (2007), DelNegro and Eusepi (2011) and Milani (2011), among others, macro shocks include the well-known and extensively studied monetary policy, demand and supply shocks. In contrast, expectations shocks, sometimes labeled as non-fundamental shocks, are driven by psychological factors or market sentiment. In a medium scale structural VAR model for US data from

[1]The FED defines anchored longer-term inflation expectations as well as medium-term inflation expectations not larger than 2.5% as two explicit criteria to maintain the federal funds rate at the zero lower bound, see FED (2012) and also ECB (2013).

1950-2000, Leduc et al. (2007) find that an inflation expectations shock leads to a long-lasting increase in actual inflation via an accommodative monetary policy. The authors interpret the finding as evidence in favor of an inflation trap mechanism, see Chari et al. (1998). In a similar model context, Clark and Davig (2011) attribute most of the decline in the volatility of US inflation expectations since the '80s to smaller expectations shocks. They explain the smaller shocks by the increased stability of the market perceived inflation target. In the context of the Great Recession and subsequent market crises we ask: How does the relative importance of macro and expectations shocks change during the Great Recession and European sovereign debt crisis?

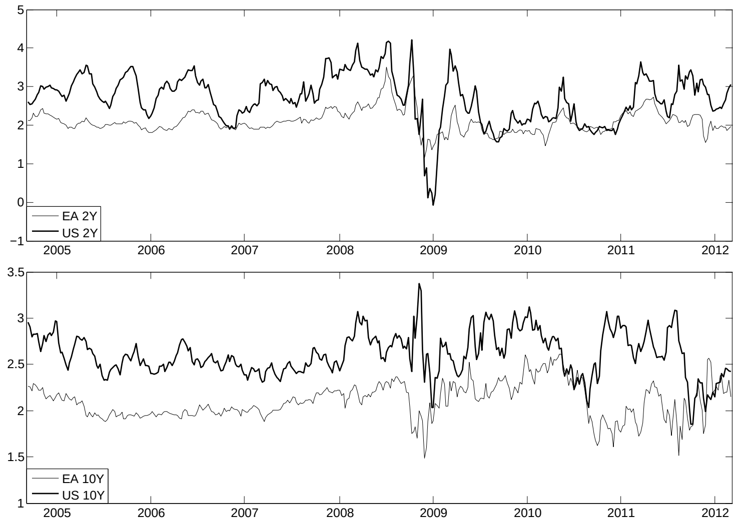
We provide answers to these questions for US and Euro Area (EA) inflation expectations based on a parsimonious structural VAR model. Our choice of variables builds on Beechey et al. (2011) and the proposition that short horizon inflation expectations are strongly driven by macro shocks, whereas at long horizons the impact of macro shocks has decayed. In a sample of weekly data from 2004 to 2012, we use an inflation expectations measure over a two year expectations horizon to extract macro shocks. Expectations shocks, which are assumed to dominate long horizon expectations, are drawn from forwards of inflation expectations in nine years for one year. The short and long horizon US and EA expectations are extracted from spreads of nominal and inflation-indexed government bonds. To control for remaining risk premia, adjustments of the spreads are taken as suggested by Pflüger and Viceira (2011) and Gürkaynak et al. (2010a). Dynamics due to oil prices and other commodities are captured by adding a commodity futures index as a fifth variable to the VAR. Our econometric approach is related to the structural VAR of Stock and Watson (2005) who use short-run restrictions to identify domestic and foreign shocks of GDP series. However, in a model with financial markets' inflation expectations and commodity futures it appears too restrictive to prevent contemporaneous adjustments. Instead of putting exclusion restrictions, we follow Rigobon (2003) and exploit the heteroscedasticity of the data. To allow for endogenous changes in the variance, we employ the Markov switching structural VAR model of Lanne et al. (2010). We test identifying conditions as described by Lütkepohl and Netšunajev (2014). Herwartz and Lütkepohl (2014) point out that the procedure of attaching labels to shocks is generally much more involved compared to classical identifying techniques. In this paper, we conduct regressions related to the instrument approach of Stock and Watson (2012) to learn about the economic nature and origin of shocks. Instruments are forecast errors of US and EA specific macroeconomic data releases. In combination with impulse responses and forecast error variance decompositions, we attain a solid ground to confirm the identification of US and EA specific macro shocks, expectations shocks and a global shock.

In line with empirical evidence about strong international comovements in actual inflation rates, we find that foreign shocks account for up to 73% of US and 63% of EA short horizon inflation expectations. The strong interlinkages in short horizon expectations are mainly driven by the global commodity price based shock. Our finding adds to Mumtaz and Surico (2012) and Ehrmann et al. (2014) that oil prices not only play a key role for the international dynamics of inflation rates but also for the dynamics of inflation expectations. In contrast to short horizon inflation expectations, expectations at long horizons are far less determined by foreign shocks. For example, only 6% of the variance of EA long horizon inflation expectations is explained by foreign shocks. Along with non-significant impulse responses to foreign macro shocks and the global commodity price based shock, this finding indicates that expectations over long expectations horizons can be labeled *local*.

We identify a large negative US macro shock whose occurrence coincides with the outbreak of the Great Recession in 2008 and causes a strong drop in short horizon expectations. Consequently, the percentage of variances explained by US and EA macro shocks peaks around the beginning of the Great Recession. In contrast, expectations shocks are most influential during times of the subsequent European debt crisis. In particular, larger EA expectations shocks translate to a 13 times larger shock variance compared to a pre-crisis period. However, the relative importance of expectations shocks for short horizon expectations remains with less than 7% relatively small. Our finding paves the way to the discussion about inflation traps: Increased expectations shocks, in particular in the EA, raise the risk of becoming self-fulfilling and feeding into the volatility of the economy. Our results suggests that transmissions in line with inflation traps have not materialized.

The rest of the paper is organized in four upcoming sections. Section 2 presents the data. Section 3 introduces the Markov switching SVAR model. The main part is Section 4. We first describe the estimation and identification and then present the results in terms of impulse responses and a forecast error variance decomposition. Section 5 concludes.

Figure 1: US and EA short and long horizon inflation expectations.



Notes: Two-year spot rate (upper figure) and one-year forward nine years ahead (lower figure). Weekly averages (Monday to Friday) of adjusted break-even inflation (BEI) rates (391 observations). For illustration purposes, adjusted BEI rates are centered around the sample mean of inflation in the EA (2.1%) and US (2.6%).

2 Data

Opposed to actual inflation rates, inflation expectations are not directly observable. A number of different measures exist that can be grouped into survey and financial market based measures. In this paper, we refer to financial market measures as they provide timely information about inflation expectations over a variety of expectations horizons.

The spread between yields of nominal and real (inflation-indexed) government bonds, known as break-even inflation, is the basis of our expectations data. Because of differences in risk premia between nominal and real bonds, break-even inflation rates are not a pure measure of inflation expectations. Adjustment procedures of Gürkaynak et al. (2010a), Christensen et al. (2010) or **?** are advocated to obtain valid expectations. In this paper, we study weekly US and EA data in the time period from September 2004 to March 2012. A two-year spot rate and a one-year forward nine years ahead model the short and long expectations horizons. While the spot rate is meant to capture drivers important for building expectations over short horizons, the forward is meant to emphasize important drives for building long horizon expectations. We follow Gürkaynak et al. (2010a) and adjust each break-even inflation rate by regressions on country and horizon specific risk measures, compare also Söderlind (2011). The residuals of such regressions constitute the inflation expectations measure used in our structural VAR analysis.[2] To account for a global driver of inflation expectations, we follow results provided by Leduc et al. (2007) and Ehrmann et al. (2014) and incorporate global commodity prices given by the S&P GSCI index as a fifth variable.[3]

Figure 1 illustrates the sample paths of the inflation expectations measures. Week-by-week expectations appear quite persistent. Conventional unit root tests suggest that the expectations measures as well as the commodity price index are stationary. The figure indicates that US expectations are more volatile than EA expectations. For the whole sample period, the standard deviation of the two-year US expectations is with 0.64 percentage points twice as large as corresponding EA expectations. Standard deviations of actual inflation rates in the US (1.6 percentage points) and EA (0.9 percentage points) share a very similar relative order of magnitude. Overall, a heteroscedastic pattern is clearly visible in the sample paths. In the following, we aim at exploiting the heteroscedasticity to identify the structural drivers behind inflation expectations.

3 The Markov switching SVAR model

The identification through heteroscedasticity is a powerful option to support identification of shocks in SVAR models. In comparison to classical identifying techniques like short run, long run or sign restrictions, the identification through heteroscedasticity is a more data oriented approach. This is also in sharp contrast to the identification strategies for latent dynamic factor models, previously applied to inflation series in e.g. Mumtaz and Surico (2012), where factor loadings are restricted to zero such that country specific factors are easily characterized by having no impact on foreign inflation. With the SVAR model and the identification through heteroscedasticity, we attempt to

[2]US BEI rates are taken from the database of Gürkaynak et al. (2010a). EA BEI rates are obtained from the ECB and contain German, French and Italian bonds. More details about the adjustments are provided in Appendix A.

[3]The S&P GSCI index tracks global futures prices for agricultural goods, energy and industrial metals. The index is provided by the Macrobond database. We also tried other global price measures like oil prices. Results reported in Section 4 remain very similar.

explore transmission channels and the economic nature of driving forces more deeply. We let the data speak about the statistical identification and check in a second step whether some economic meaning can be attached to the individual structural shocks. In general, our statistical procedure allows some country specific shock to transmit to foreign inflation expectations.

Given our data vector of two- and ten-year US and EA inflation expectations and commodity prices, $Y_t = (\text{EA2Y US2Y EA10Y US10Y Cmdty})'$, we aim at identifying shocks ε_t through a structural VAR model with p lags:

$$Y_t = \nu + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + B\varepsilon_t, \tag{1}$$

where ν is a constant intercept and the A_js ($j = 1, \ldots, p$) are 5×5 coefficient matrices. We follow Lanne et al. (2010) and model the heteroscedasticity of ε_t via a discrete Markov process s_t with states $1, 2, ..., M$, transition probabilities $p_{ij} = \Pr(s_t = j | s_{t-1} = i)$, $i, j = 1, \ldots, M$ and conditional distribution $\varepsilon_t | s_t \sim N(0, \Lambda_{s_t})$. The matrix $\Lambda_{s_t} = \text{diag}(\lambda_1, ..., \lambda_5)$ is normalized such that the $\varepsilon_{t,k}$, $k = 1, 2, .., 5$, have unit conditional variance in the first state. Standard matrix algebra determines the matrix B of impact effects:

$$\Sigma_1 = BB', \quad \Sigma_{s_t} = B\Lambda_{s_t}B', \quad s_t = 2, 3, ..., M\ , \tag{2}$$

where the reduced form error covariance matrix Σ_{s_t} is conditioned on the same process s_t as its structural counterpart Λ_{s_t}. The standard linear combination $\varepsilon_t = B^{-1}U_t$ gives the relation between structural and reduced form errors. The decomposition (2) imposes testable restrictions on the covariance matrices. In case of $M > 2$, it is possible to check whether the data is compatible with the decomposition and, thus, a time-invariant B can be used to transform reduced form errors into structural shocks. Lanne et al. (2010) shows that the model (1) and decomposition (2) give a unique (apart from ordering and sign) B (and thus ε_t) if structural shocks' variances are distinct across variables and states, i.e. for any two subscripts $k, l \in \{1, ..., 5\}$, $k \neq l$, there is a $j \in \{2, ..., M\}$ such that $\lambda_{jk} \neq \lambda_{jl}$.

Besides approving that the structural shocks are unique, orthogonal and heteroscedastic, the statistical procedure does not necessarily provide economically interpretable shocks. The motivation behind (1) is that the approach extracts not only statistically unique shocks but also decomposes the distinctive natures of the data Y_t. Since the distinguishing features of the data are the expectations horizons (economic content) and geographical source (US, EA and global), the different $\varepsilon_{t,k}$, $k = 1, 2, .., 5$ are meant to isolate some of these different characteristics. In accordance with implications of macroeconomic models presented by Beechey et al. (2011) and related economic intuition, we evaluate the economic meaning of shocks in Section 4.[4]

Stemming on the conditional normality of the reduced form residuals, we estimate the MS-SVAR model via maximum likelihood. The full algorithm can be found in the Appendix B. Tests for statistical identification and confidence bands for impulse response function are computed as suggested in Lütkepohl and Netšunajev (2014).

4 US and EA inflation expectations spillovers

In this section, we document the model selection procedure and how we achieve the identification of macro and expectations shocks and their US, EA or global origin. Given the identified structural shocks, we study their impact on US and EA inflation expectations via impulse responses and the variance decompositions.

4.1 Model specification and identification

To specify an appropriate model for the identification of structural shocks from the inflation expectations and commodity price index, we first choose the lag length of a reduced form VAR with constant parameters for the whole sample period from 2004 to 2012. We follow the suggestion of the Schwarz criterion (SC) and continue with a VAR with three lags. We then implement the switching variance for different numbers of states M. Determination of the number of states by means of information criteria has been analyzed by Psaradakis and Spagnolo (2003, 2006). The information criteria are reported to perform well when the parameter changes are not too small. Building on these findings, we base the selection of M on the information criteria. Table 1 shows the log-likelihood and values of the Akaike (AIC) and SC for different

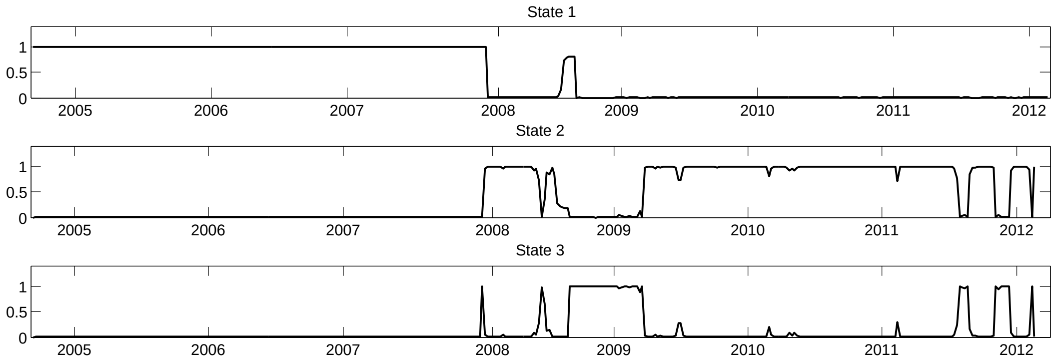
[4]Due to the numerical complexity of the estimations and the weekly data frequency, our empirical strategy does not consider variables like GDP, inflation, unemployment or interest rates. We stress similarities of structural shocks derived from (1) with shocks of reduced rank SVARs and structural FAVARs. The basic idea is that shocks in (1) combine standard economic shocks relevant for inflation expectations. For interpretations see also Appendix C.

Table 1: Markov switching VAR model selection.

Model	$\log L_T$	AIC	SC
VAR(3) without MS	2012	-3834	-3458
MS(2)-VAR(3)	2343	-4466	-4030
MS(3)-VAR(3)	2451	-4652	-4157*
MS(4)-VAR(3)	2472	-4664*	-4109

Notes: L_T is the value of the likelihood function, AIC $= -2\log L_T + 2\times\#$ free parameters, SC $= -2\log L_T + \log T\times\#$ free parameters. Sample: 2004 - 2012 (T = 391 obs.).

Figure 2: State probabilities of MS(3)-VAR(3) model.



Notes: Three volatility regimes: state 1 the lowest, state 3 the highest volatility.

models. Clearly, the likelihood is increasing in the flexibility of the model. We choose the model with three variance states since the MS(3)-VAR(3) is preferred by the SC.[5]

The estimated smoothed state probabilities of the MS(3)-VAR(3) model are shown in Figure 2. State 1 is the lowest volatility regime and State 3 the highest volatility regime. It can be seen that the first part of the sample until late 2007 is associated with state 1, while state 2 and 3 dominate the second part of the sample. The period since 2008 is well known to coincide with the global financial crisis, the global recession and the European sovereign debt crisis. We label state 1 as a non-crisis state and state 2 and 3 as crisis states. State 3 captures the timing of key events like the failure of the investment banks Bear

[5]Note that with four regimes the statistical identification is not obvious and the states are more difficult to label. A two regime model provides the same qualitative results presented in the next subsection.

Table 2: Tests for equality of structural variances across states.

H_0	LR statistic	p-value
$\lambda_{21} = \lambda_{22},\ \lambda_{31} = \lambda_{32}$	15.6	0.00
$\lambda_{21} = \lambda_{23},\ \lambda_{31} = \lambda_{33}$	36.8	0.00
$\lambda_{21} = \lambda_{24},\ \lambda_{31} = \lambda_{34}$	12.9	0.00
$\lambda_{21} = \lambda_{25},\ \lambda_{31} = \lambda_{35}$	25.7	0.00
$\lambda_{22} = \lambda_{23},\ \lambda_{32} = \lambda_{33}$	41.0	0.00
$\lambda_{22} = \lambda_{24},\ \lambda_{32} = \lambda_{34}$	2.95	0.23
$\lambda_{22} = \lambda_{25},\ \lambda_{32} = \lambda_{35}$	48.8	0.00
$\lambda_{23} = \lambda_{24},\ \lambda_{33} = \lambda_{34}$	26.4	0.00
$\lambda_{23} = \lambda_{25},\ \lambda_{33} = \lambda_{35}$	48.8	0.00
$\lambda_{24} = \lambda_{25},\ \lambda_{34} = \lambda_{35}$	43.2	0.00

Notes: Likelihood Ratio (LR) tests for equality of normalized structural variances ($\lambda_{s_t,k}$) across states $s_t = 2, 3$ and variables $k = 1, ..., 5$ of MS(3)-VAR(3).

Stearns (March 2008) and Lehman Brothers (September 2008), the home loan mortgage corporation Fannie Mae and Freddie Mac (July 2008) as well as the intensification of the European sovereign debt crisis, affecting Italy and Spain and coupled with increased banking sector strains, from mid-2011 on.

Statistical identification

As reviewed in Section 3, we aim at using the heteroscedasticity governed by the Markov states for identification purposes. Thus, the variances of shocks, $\mathrm{E}(\varepsilon^2_{t(s_t),k}) = \lambda_{s_t,k}$, with shock number $k = 1, ..., 5$, and volatility state $s_t = 2, 3$, have to be sufficiently distinct, see Section 3. We follow Lanne et al. (2010) and Lütkepohl and Netšunajev (2014) and verify that condition by pairwise LR-tests. Results presented in Table 2 indicate sufficient heterogeneity in the variances. It appears that with a p-value of 0.23 only shock $\varepsilon_{t,3}$ and $\varepsilon_{t,4}$ are difficult to distinguish. The point estimates reported in Table 4 show that $\lambda_{s_t,2}$ and $\lambda_{s_t,4}$ are relatively similar compared to other pairs. However, in state 2 point estimates differ by a factor of 2 and we will demonstrate in the following that the two shocks have very different characteristics, thus, pose no problem for identification. Despite distinct variances, we check the validity of decomposition (2) by a LR-test. A p-value of 0.37 supports that the matrix of impact effects B of structural shocks can be considered state-invariant in the three state model. Hence, we conclude that the shocks are statistically identified. Note that for the model with four Markov states, preferred by the AIC (Table 1), these requirements for the statistical identification are not met.

Labeling of identified shocks

To verify whether we can attach some economic meaning and geographical origin to the statistically identified shocks, we first set up a regression study. In separate regressions, each structural shock is modeled as a dependent variable. The choice of explanatory variables is mainly motivated by Beechey et al. (2011) and the idea that a dominating force behind short horizon inflation expectations are demand, supply and monetary policy shocks, whereas long horizon expectations should be mostly insensitive to these shocks. Thus, distinct relations between structural shocks and certain US and EA proxies for demand, supply and monetary policy shocks (macro shocks in short) may support the economic interpretation. We utilize the difference between officially released economic outcomes and a respective expected value as a measure of macro shocks. The set of macro instruments is uniform in all regressions and contains the surprise component of consumption expenditure, income, unemployment, GDP, industrial production, trade balance, inflation, productivity and monetary policy announcements for the US and EA, respectively. Market expectations are measured by using the Consensus mean forecast published by Bloomberg the Friday before each macroeconomic data release.[6] In total we have five regressions with 18 surprise variables on a weekly basis. Our investigations focus on two joint parameter tests.

- H_0^{US}: $\beta_1 = 0$
  US instruments have no explanatory power for $\varepsilon_{t,k}$,
- H_0^{EA}: $\beta_2 = 0$
  EA instruments have no explanatory power for $\varepsilon_{t,k}$, $k = 1, ..., 5$.

Table 3 shows the regression equation and test results. Further details and interpretations are provided in Appendix C. The regressions contribute to the economic interpretation of the structural shocks. The two tests reflect that shock 1 responses significantly to surprises about EA macroeconomic releases but not to US releases. Hence, we provisionally label structural shock 1 as a "EA macro shock". We find that important drivers are releases about EA inflation and government consumption. In contrast to shock 1, for shock 2 the Null that US macroeconomic surprises have no impact is rejected, but

[6] See further information about surprise variables and the regressions in Appendix C.

Table 3: Wald test from regressions with structural shocks on macro surprises (X).

$$\varepsilon_{t,k} = \beta_1' X_t^{(\mathrm{US})} + \beta_2' X_t^{(\mathrm{EA})} + u_t$$

	$H_0^{US} : \beta_1 = 0$	$H_0^{EA} : \beta_2 = 0$
$\varepsilon_{t,1}$	2.12 (0.99)	**19.3** (0.03)
$\varepsilon_{t,2}$	**18.2** (0.03)	8.48 (0.49)
$\varepsilon_{t,3}$	1.77 (0.99)	1.60 (0.99)
$\varepsilon_{t,4}$	13.5 (0.14)	8.58 (0.48)
$\varepsilon_{t,5}$	**112** (0.00)	**53.5** (0.00)

Notes: Bold Chi-square-test statistics indicate rejections of H_0^j, j=EA, US. p-values- 9 degrees of freedom- are given in parentheses. Estimated standard deviations are based on HAC standard errors. Sample: 2004 - 2012 (T = 388 obs.).

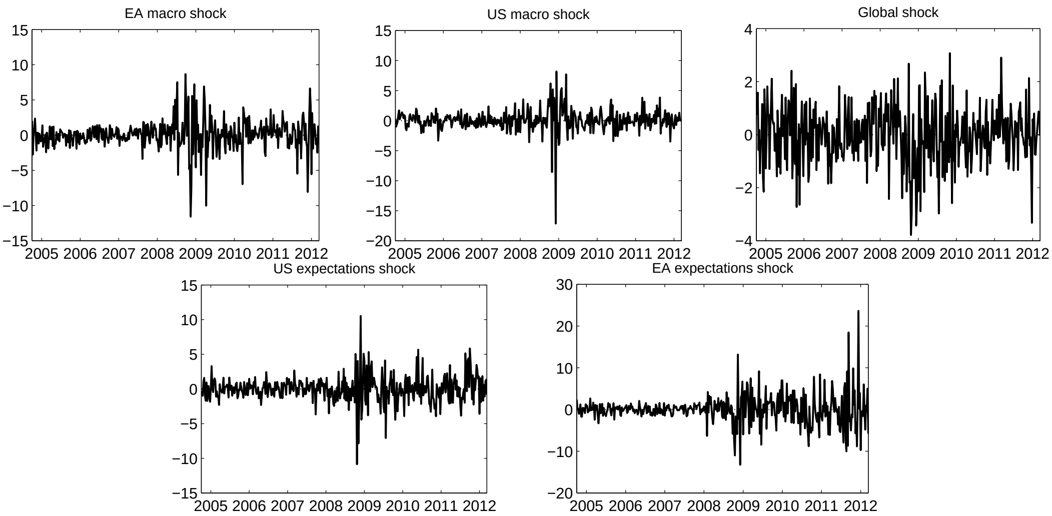
we can not reject the insensitivity to EA surprises. Thus, for shock 2 we attach the provisional label "US macro shock". Major drivers are news about US inflation and FED policy announcements. Shock 3 and 4 do not respond to either US and EA macroeconomic surprise components, so they appear as candidates for originating at longer expectations horizons. We label them "expectations shocks". However, from the regression results we are not able to verify their origin.[7] Finally, shock 5 responses to a mixture of US and EA releases, including components of FED and ECB policy announcements, US GDP and US and EA industrial production. We propose to label the fifth structural shock a "global macro shock", capturing the global component of news releases.

As indicated by the R^2s the overall explanatory power of the regressions are rather low. This finding is not surprising in light of related regressions with break-even inflation rates by Gürkaynak et al. (2010b) and may reflect omitted surprise variables.[8] It should be acknowledged that a different set of surprise

[7] Note that the statistical identification is apart from ordering and sign. Thus, the ordering of structural shocks is not necessarily reflecting the ordering of variables in the data vector Y_t, see Section 3.

[8] Not that in the news regression context the omission is not likely to cause a bias of OLS-β estimates since, given the nature of forecast errors, surprise variables are usually mutually uncorrelated.

Figure 3: Structural shocks of the MS-SVAR model.



variables may produce less clear-cut results. However, we pick most widely used and available data releases and find test results to be robust against moderate variations in the sample length.

To further support our economic labels, we report standard deviations and the relative variances (λ) of structural shocks in Table 4. Two characteristics distinguish US and EA specific macro shocks. First, US macro shocks are much larger in absolute size than EA macro shocks, e.g. the standard deviation in the non-crisis state in the US is almost three times larger than in the EA. Second, the relative variance of EA macro shocks increases stronger in crisis times (state 2 and 3). The increase relative to state 1 in the EA is 22.8%, in the US 17.7%. These two distinguishing characteristics of the US and EA macro shocks are also present in the US and EA macroeconomic surprise variables used as explanatory variables in the regressions, compare related descriptive statistics reported by **?**. This gives further support to our economic labeling of the first two shocks. We carry over this result to the expectations shocks and label shock 3 with the smaller standard deviation and larger relative variances the "EA expectations shock" and shock 4 the "US expectations shock". We define a expectations shock as a shock that can not be explained by macroeconomic surprise variables but should play an important role for long horizon inflation expectations. A favorable expectations shock moves inflation expectations in the direction of an officially announced or market perceived inflation

Table 4: Standard deviation and relative variance (λ) of structural shocks (ε).

		Macro shocks		Expectations shocks	
State		EA (k=1)	US (k=2)	ECB (k=3)	FED (k=4)
1	$\mathrm{sd}(\varepsilon_{t(1),k})$	0.045	0.139	0.030	0.062
2	$\mathrm{sd}(\varepsilon_{t(2),k})$	0.078	0.178	0.107	0.118
	$\lambda_{2,k}$	3.03 (0.58)	1.63 (0.32)	12.8 (2.69)	3.65 (0.70)
3	$\mathrm{sd}(\varepsilon_{t(3),k})$	0.214	0.586	0.219	0.231
	$\lambda_{3,k}$	22.8 (7.88)	17.7 (4.29)	53.5 (15.0)	14.1 (4.09)

Notes: $\mathrm{sd}(\varepsilon_{t(s_t),k})$ are standard deviations of structural shocks calculated via $\varepsilon_t = B^{-1}U_t$, with B^{-1} having normalized unit main diagonal elements. λs in State 1 are normalized to one. Standard deviation of estimated λs in parentheses.

target whereas an increasing variance of expectations shocks is interpreted as higher uncertainty about the target. In crisis periods, with central banks' key interest rates at the zero lower bound and implemented non-standard policy measures, an increase in uncertainty about the credibility of inflation targets, as documented in Table 4, appear natural. The EA expectations with an increase of the structural error's variance of up to 53.5% is much stronger affected compared to the 14.1% increase in US expectations shocks. One possible explanation for this gap is the more controversial discussions about ECB policy measures in the media, which may have affected financial market uncertainty to a large extend.

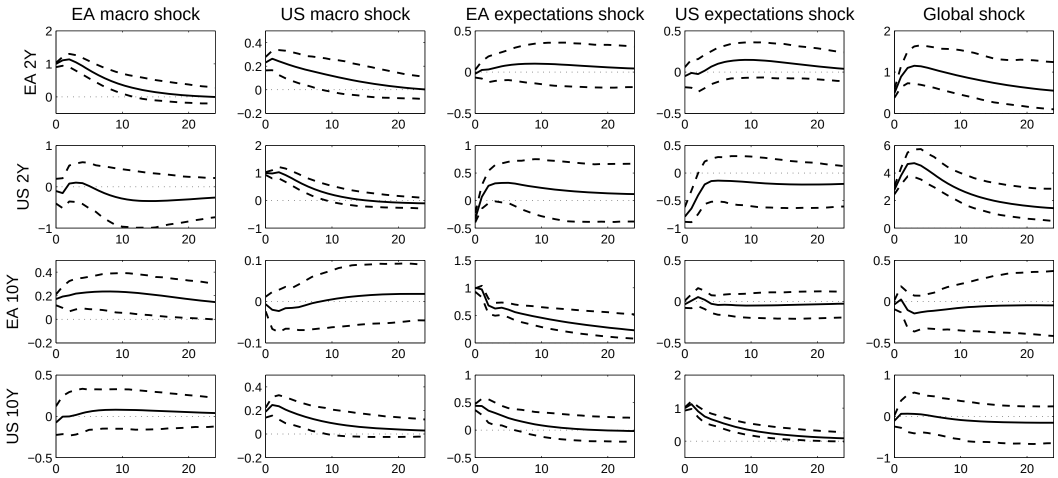
Having in mind the labeling of US and EA specific shocks and the global shock, we continue the analysis of the MS-SVAR model.

4.2 Impulse response analysis

We study how the structural shocks affect the level of short and long horizon inflation expectations in the US and EA through normalized impulse responses.[9]

[9] To check the robustness of our results, we estimate classical SVARs identified via zero restrictions on contemporaneous effects for two subsamples (before and after 2008). Zero restrictions are chosen as indicated by the impulse responses of the MS-SVAR model. These restrictions are over-identifying and supported for the two subsamples by conventional tests. Most impulse responses of the separately estimated models are not significantly different for the two sample periods. Main economic conclusion can be supported.

Figure 4: Impulse responses of inflation expectations.



Notes: MS(3)-SVAR(3). Impulse responses to a one unit structural shock with 95% bootstrap confidence bands based on 1000 replications. Full sample period (391 obs.).

The two-year inflation expectations

The first two rows of Figure 4 display how the US and EA specific and the global shocks transmit to short horizon inflation expectations. Similar to spillovers between US and EA financial markets, studied by Ehrmann et al. (2011), impulse responses indicate that US macro shocks significantly affect EA expectations (first row, second column) but not vice versa (second row, first column). The global macro shock has a significant and persistent impact on both US and EA inflation expectations (first and second row, fifth column). The expectations shocks appear to be less important at short expectations horizons. However, US expectations respond significantly to US expectations shocks (second row, fourth column). The negative but fast decaying impact may reflect either distinct levels of perceived inflation targets at short and long horizons or a situation where the short inflation expectations are systematically above (below) a perceived target and long horizon expectations below (above) the target.[10]

[10]Note that the FED announced its official inflation target of 2% in 2012 – the ending of our sample period. The finding may reflect uncertainty about the level of the target. The negative impact appears quite robust across different specifications, e.g. in a two state MS-SVAR model and the model (robustness check) discussed in footnote 9.

The ten-year inflation expectations
Responses of long horizon inflation expectations are depicted in the third and fourth row of Figure 4. In contrast to short horizon inflation expectations, long horizon inflation expectations are not significantly affected by the global macro shock. Domestic shocks appear to play an important role. With respect to the anchoring criteria defined by Gürkaynak et al. (2010b), impulse responses indicate that US and EA inflation expectations are strongly anchored with respect to foreign macro shocks (fourth row, first and fifth column; third row, second and fifth column). Domestic macro shocks have a significant impact (fourth row, second column; third row, first column). From the fast decaying impulse responses, we conclude that inflation expectations are firmly anchored in both the US and EA, compare Strohsal and Winkelmann (2015).

4.3 Variance decomposition

Having studied the impulse responses to structural shocks, we now turn to assess their relative importance for the variance of US and EA inflation expectations. Since variances change across the three Markov states, spillovers vary across the non-crisis (state 1) and crisis states (state 2 and 3). Spillovers are defined as the percentage of the US (EA) inflation expectations variance explained by both EA (US) shocks and the global shock. Results are summarized in Table 5.

The non-crisis period
In line with findings on actual inflation, our results show that short horizon inflation expectations are strongly affected by foreign structural shocks. In the non-crisis state 73.7% of the variance of US inflation expectations is explained by spillovers. For EA expectations the percentage is with 63.2% similarly large. Spillovers have the same order of magnitude as related global factors of actual inflation studied by Neely and Rapach (2011) and Mumtaz and Surico (2012). The SVAR model further reveals that for US short horizon expectations the main source of spillovers is the global macro shock (71.3%). EA specific shocks play with 2.4% only a marginal role for US expectations. On the contrary, EA inflation expectations are with 15.1% of its variance more exposed to US shocks. However, also for EA short horizon inflation expectations the global macro shock still plays the most significant role (48.1%).

At long expectations horizons the picture is materially different. Spillovers

Table 5: Variance decomposition of inflation expectations.

		EA 2Y			US 2Y			EA 10Y			US 10Y		
Volatility states		1	2	3	1	2	3	1	2	3	1	2	3
Macro shocks	EA	36.5	58.4	66.8	1.9	4.4	5.9	28.2	9.2	15.4	1.0	0.9	1.4
	US	13.3	11.4	18.9	23.8	30.2	58.1	1.7	0.3	0.7	19.4	9.3	22.1
	Global	48.1	24.4	10.8	71.3	53.5	27.6	3.6	0.4	0.2	5.0	1.4	0.9
Exp shocks	EA	0.3	2.2	1.4	0.5	4.6	3.4	65.1	89.6	83.2	3.2	12.1	11.0
	US	1.8	3.6	2.1	2.6	7.3	5.0	1.3	0.5	0.4	71.3	76.4	64.6
Spillover		63.2	39.4	31.8	73.7	62.5	36.9	6.6	1.2	1.3	9.2	14.4	13.3

Note: Percentage of the inflation expectations variance explained by the structural shocks (ε) in States 1 (lowest volatility, non-crisis state) to state 3 (highest volatility, crisis state). Spillovers refer to aggregated contributions of foreign shocks. Calculated from forecast error variance decomposition at 100 weeks horizon.

account for only 9.2% of the variance of US and 6.6% of EA inflation expectations. Inline with ideas formalized by **?** and Beechey et al. (2011), our results indicate that the expectations shocks are the main driver of long horizon inflation expectations. The US expectations shock accounts for 71.3% of US expectations while 65.1% of the variance of EA inflation expectations is explained by EA expectations shocks. In the non-crisis state, transmissions of expectations shocks between the US and EA are negligible.

Crisis periods

The variance decomposition indicates that spillovers decrease in crisis times. We find that the main driver of the decline is the global macro shock whose impact on short horizon expectations drops down to one-third for the US and one-fourth for the EA. The decline is slightly compensated by increasing transmissions of US and EA specific shocks, e.g. the explanatory power of EA macro and expectations shocks for US short horizon expectations increases up to 7 percentage points (state 1 vs. 3). Given the relative nature of the variance decomposition, decreasing spillovers imply an increasing role of domestic shocks. The variance decomposition of short horizon EA expectations provides an example. The variance explained by EA macro shocks almost doubles in crisis times and accounts for 66.8% in state 3. This pattern suggests that during the global financial crisis, the great recession and the European sovereign debt crisis the relative exposure of inflation expectations to foreign shocks has declined resulting in a stronger focus on the domestic economy.

The US long horizon expectations provide an exemption to the decreasing spillovers. US expectations are with a slight increase from 9.2% up to 14.4% stronger affected by foreign shocks during crisis times. The key driver of the elevated spillovers are the EA expectations shocks, reflecting the impact of the European sovereign debt crisis on US expectations. Overall, the main result of strong international components in short horizon inflation expectations and rather local components in long horizon inflation expectations can be confirmed for the crisis period.

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Table 6: Regressions for risk adjustments of BEI rates.

	EA		US	
	2Y	10Y	2Y	10Y
<u>AAA-spread:</u>				
EA(3Y), US (3Y)	−0.51	–	−0.36	–
	(0.07)		(0.10)	
EA(10Y), US(10Y)	–	−0.18	–	−0.11
		(0.08)		(0.04)
<u>Volatiliy:</u>				
VSTOXX	−0.01	0.01	–	–
	(0.00)	(0.00)		
VIX	–	–	−0.07	0.01
			(0.01)	(0.00)

Notes: Sample period 2004 to 2012. Heteroscedasticity adjusted p-values are given in parentheses.

A Adjustments of BEI rates

We adjust the spread of nominal and inflation-indexed interest rates (BEI rates) by regressing them on risk measures. The adjusted BEI rate is then given by the residual of this regression. If $risk_t$ contains the risk measures and π_t^e represents the adjusted BEI rate, we have $\pi_t^e = BEI_t + \delta' risk_t$, where δ is a vector of coefficients. This is a common approach which is used, among others, by Chen et al. (2007) who estimate liquidity premia in corporate yield spreads and Gürkaynak et al. (2010a) or Pflüger and Viceira (2011) who apply this approach to the yield spread of nominal and inflation-indexed government bonds.

Our choice of measures is mainly motivated by the discussion in Christensen and Gillan (2012). One country specific as well as horizon specific measure is given by the spread between AAA rated corporate bond yields and nominal government bond yields. The second measure captures the overall uncertainty in the markets. We utilize the implied volatility of S&P 500 index options (VIX) for US BEI rates and the implied volatility of EURO STOXX index options (VSTOXX) for EA BEI rates. The regression results are shown in Table 6.

Short horizon BEI rates are with R^2s of 0.65 (EA) and 0.72 (US) stronger adjusted than long horizon BEI rates ($R^2 = 0.06$ for both US and EA BEI rates). The liquidity reduce the correlations between the series.

B MS-SVAR estimation steps

The appendix describes the expectation maximization (EM) algorithm for the Markov switching SVAR model including parameter choices for the empirical application. The notation is based on Krolzig (1997) and Herwartz and Lütkepohl (2014).

- **Definitions**
  - The baseline model is a VAR(p) of the form:
    $y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t$,
    with $t = 1, ..., T$ and y_t of dimension K.
  - $\xi_t = \begin{pmatrix} I(s_t = 1) \cdots I(s_t = M) \end{pmatrix}'$,
    $E(\xi_t) = \begin{pmatrix} Pr(s_t = 1) \cdots Pr(s_t = M) \end{pmatrix}'$,
    with states $s_t = 1, ..., M$ and $I()$ an indicator function which takes value 1 if the statement in the argument is true and 0 otherwise.
    $\xi_{t|s} = E(\xi_t|Y_s) = \begin{pmatrix} Pr(s_t = 1|Y_s) \cdots Pr(s_t = M|Y_s) \end{pmatrix}'$, with $Y_s = (y_1, ..., y_s)$ and P the transition matrix, which yields $\xi_{t+1|t} = P\xi_{t|t}$, for $t = 0, 1, ..., T-1$.
  - $\eta_t = \begin{pmatrix} f(y_t|s_t = 1, Y_{t-1}) \cdots f(y_t|s_t = M, Y_{t-1}) \end{pmatrix}'$,
    where $f()$ is the conditional distribution function:
    $f(y_t|s_t = m, Y_{t-1}) = (2\pi)^{-K/2} \det(\Sigma_m)^{-1/2} \exp(-0.5 u_t' \Sigma_m^{-1} u_t)$,
    and covariance matrices have decomposition $\Sigma_1 = BB', \Sigma_m = B\Lambda_m B'$ for $m = 2, ..., M$.

  Notation:
  $\odot$ elementwise multiplication,
  $\oslash$ elementwise devision,
  $\otimes$ Kronecker product,
  I_K is a $K \times K$ dimensional identity matrix,
  $1_M = (1, ..., 1)'$ is a $M \times 1$ dimensional vector of ones,
  $\theta = \text{vec}(v, A_1, A_2, ..., A_p)$ is the parameter vector,
  $Z_{t-1}' = (1, y_{t-1}', y_{t-2}', ..., y_{t-p}')$ is the matrix of ones and lagged observations.

- **Initial values**

  The following starting values are used for the iterations:

  - $P = M^{-1} 1_M 1_M'$

- $\hat{\theta} = \text{vec}(\hat{v}, \hat{A}_1, ..., \hat{A}_p) = \left[\sum_{t=1}^{T} Z_{t-1}Z'_{t-1} \otimes I_K\right]^{-1} \sum_{t=1}^{T} (Z_{t-1} \otimes I_K)y_t$
- $B = T^{-1}(\sum_{t=1}^{T} \hat{u}_t\hat{u}'_t)^{1/2} + B_0$, where $\hat{u}_t = y_t - (Z'_{t-1} \otimes I_K)\hat{\theta}$ and B_0 is a matrix of random numbers coming form standard normal distribution and scaled by a factor of 10^{-5}.
- $\Lambda_1 = I_K, \Lambda_m = c_m I_K, m = 2, ..., M$ with $c_2 = 0.4, c_3 = 0.16$ for this application.
- $\xi_{0|0} = M^{-1}1_M$

• **Expectation step**

For given $P, \theta, \Sigma_m, m = 1, 2, ..., M$ and $\xi_0 = \xi_{0|0}$ the following parameters are computed:

- η_t for $t = 1, 2, ..., T$,
- $\xi_{t|t} = \frac{\eta_t \odot P\xi_{t-1|t-1}}{1'_M(\eta_t \odot P\xi_{t-1|t-1})}$, for $t = 1, 2, ..., T$.
- $\xi_{t|T} = (P'(\xi_{t+1|T} \oslash P\xi_{t|t})) \odot \xi_{t|t}$, for $t = T - 1, ..., 0$.
- $\xi^{(2)}_{t|T} = \text{vec}(P') \odot ((\xi_{t+1|T} \oslash P\xi_{t|t}) \otimes \xi_{t|t})$, for $t = 1, ..., T - 1$.

• **Maximization step**

- Estimate P:
  $\text{vec}(\hat{P}') = \left(\sum_{t=0}^{T-1} \xi^{(2)}_{t|T}\right) \oslash \left(1_M \otimes (1'_M \otimes I_M) \sum_{t=0}^{T-1} \xi_{t|T}\right)$
- Estimate B and Λ_m:
  Define $T_m = \sum_{t=1}^{T} \xi_{mt|T}$, where $\xi_{mt|T}$ denotes the m-th element of the vector $\xi_{t|T}$. Estimation of B and Λ_m is done by minimizing the likelihood function:
- $l(B, \Lambda_2, ..., , \Lambda_M) = T \log\det(B) + \frac{1}{2}\left(B'^{-1}B^{-1}\sum_{t=1}^{T} \xi_{1t|T}\hat{u}_t\hat{u}'_t\right)$
  $+ \sum_{m=2}^{M}\left[\frac{T_m}{2}\log\det(\Lambda_M) + \frac{1}{2}tr\left(B'^{-1}\Lambda_M^{-1}B^{-1}\sum_{t=1}^{T} \xi_{mt|T}\hat{u}_t\hat{u}'_t\right)\right]$.
- Then compute:
  $\hat{\Sigma}_1 = \hat{B}\hat{B}', \hat{\Sigma}_m = \hat{B}\hat{\Lambda}_m\hat{B}'$ for $m = 2, ..., M$
- Estimates of the parameter vector θ are given by:
  $\hat{\theta} = \left[\sum_{m=1}^{M}\left(\sum_{t=1}^{T} \xi_{mt|T}Z_{t-1}Z'_{t-1}\right) \otimes \hat{\Sigma}_m^{-1}\right]^{-1} \sum_{t=1}^{T}\left(\sum_{m=1}^{M} \xi_{mt|T}Z_{t-1} \otimes \hat{\Sigma}_t^{-1}\right) y_t$

- Initial regime probabilities are updated according to:

  $\xi_{0|0} = \xi_{0|T}$

- **Convergence criteria**

  Relative change in the value of the log-likelihood function is used as convergence criteria. The log-likelihood is evaluated for given $P, \theta, \Sigma_m, m = 1, 2, ..., M$ and $\xi_{0|0}$ as follows. Compute:

  - η_t for $t = 1, 2, ..., T$,
  - $\xi_{t|t-1} = P\xi_{t-1|t-1}$, for $t = 1, 2, ..., T$,
  - $\xi_{t|t} = \frac{\eta_t \odot P\xi_{t|t-1}}{1'_M(\eta_t \odot P\xi_{t|t-1})}$, for $t = 1, 2, ..., T$.
  - Then $\log L_T = \sum\limits_{t=1}^{T} \log f(y_t|Y_{t-1})$,

    $f(y_t|Y_{t-1}) = \sum\limits_{m=1}^{M} Pr(s_t = m|Y_{t-1}) f(y_t|s_t = m, Y_{t-1}) = \xi'_{t|t-1}\eta_t.$

  Estimation of B , Λ_m and θ are iterated until convergence, i.e. relative change Δ in the log-likelihood is negligibly small (does not exceed tolerance value $\alpha = 10^{-9}$) for j-th and $(j-1)$-th rounds of iterations: $\Delta = \frac{\log L_T(j) - \log L_T(j-1)}{\log L_T(j-1)} < \alpha$.

- **Bootstrapping confidence bands for impulse responses**

  Herwartz and Lütkepohl (2014) discuss a fixed design wild bootstrap procedure for constructing confidence intervals for impulse responses in the presently considered model class. The bootstrap samples are constructed as

  $y_t^* = \hat{v} + \hat{A}_1 y_{t-1} + \cdots + \hat{A}_p y_{t-p} + u_t^*$

  where $u_t^* = \zeta_t \hat{u}_t$ and ζ_t is a random variable taking values 1 and -1, each with probability 0.5. We bootstrap parameter estimates θ^*, B^* and Λ^* conditionally on the initially estimated transition probabilities.

C Regressions with instruments

To support the interpretation and labeling of structural shocks, we regress the identified structural shocks on instruments of macroeconomic shocks. Instruments are the surprise component of data releases computed as the released value less the mean of market expectations. Expectations are submitted by financial market experts (mostly bankers) the Friday before each data release. Around 50 experts contribute to the survey of US specific releases, while for EA macro releases the number is around 30. Data is provided by Bloomberg. Instruments are constructed like forecast errors thus are mutually uncorrelated and provide information about some specific demand, supply or monetary policy shock. Instruments share common characteristics with the structural shocks since both are centered, not autocorrelated and heteroscedastic. Weekly shocks are regressed on weekly instruments. Instruments are zero in cases of no release. Regressions capture surprises about the following fundamental:

- US: Gross domestic product (GDP), industrial production (IP), urban consumer price index (CPI), unemployment rate (UEM), Output per hour (Productivity), trade balance of goods and services (Trade), consumer credit (CCredit), personal income (Income), federal funds target rate (MP).
- EA: Gross domestic product (GDP), industrial production (IP), harmonized consumer price index (CPI), unemployment rate (UEM), labor costs (Productivity), trade balance with non eurozone (Trade), consumption expenditure (CExp), government final consumption expenditure (GovC), ECB main refinancing rate (MP).

Regression results are shown in Table 7. The first two structural shocks $\varepsilon_{t,1}$ and $\varepsilon_{t,2}$ respond mainly to EA and US instruments, respectively. $\varepsilon_{t,3}$ and $\varepsilon_{t,4}$ are mostly unresponsive and $\varepsilon_{t,5}$ are sensitive to a mixture of US and EA instruments. Labels are attached as discussed in Section 4, compare also results of F-tests reported in Figure 3. R^2s are around 0.15 for $\varepsilon_{t,1}$, $\varepsilon_{t,2}$ and $\varepsilon_{t,5}$ and even smaller for the other shocks. This is not surprising since many entries of the instrument vectors are zero; e.g. GDP releases are quarterly while the dependent variable is weekly.

Shocks and regression results have the following interpretations: Significantly negative coefficient estimates indicate a reverse relation between the sign of $\varepsilon_{t,i}$ and the instrument. For example, a positive supply shock works through an unexpected increase in US productivity and results in a negative $\varepsilon_{t,2}$. As indicated by impulse responses in Figure 4, the decrease in $\varepsilon_{t,2}$ pushes

Table 7: Regressions with structural shocks and instruments.

	Structural shocks of MS-SVAR model				
	$\varepsilon_{t,1}$	$\varepsilon_{t,2}$	$\varepsilon_{t,3}$	$\varepsilon_{t,4}$	$\varepsilon_{t,5}$
US instruments:					
· MP	2.00	**3.99**	−1.28	**−3.79**	**−6.20**
	(0.63)	(0.08)	(0.78)	(0.09)	(0.00)
· Trade	0.03	0.41	0.00	0.03	−1.91
	(0.88)	(0.63)	(0.99)	(0.66)	(0.26)
· Productivity	0.05	**−0.38**	−0.04	−0.30	−0.02
	(0.88)	(0.07)	(0.95)	(0.28)	(0.97)
· CPI	0.93	**2.01**	0.35	1.47	−2.21
	(0.43)	(0.05)	(0.85)	(0.20)	(0.10)
· GDP	−0.28	0.17	−0.25	−0.55	**1.84**
	(0.46)	(0.60)	(0.76)	(0.22)	(0.00)
· IP	−0.11	−0.16	0.73	0.29	**2.53**
	(0.75)	(0.68)	(0.24)	(0.55)	(0.04)
· UEM	0.03	0.02	−0.28	0.51	0.10
	(0.55)	(0.68)	(0.88)	(0.69)	(0.20)
· CCredit	−0.01	**0.04**	−0.02	0.01	−0.01
	(0.76)	(0.06)	(0.68)	(0.72)	(0.74)
· Income	−0.02	0.56	−0.24	0.14	−0.13
	(0.96)	(0.17)	(0.82)	(0.71)	(0.88)
EA instrument:					
· MP	−0.41	0.20	−0.02	−0.84	**−3.90**
	(0.77)	(0.93)	(0.99)	(0.62)	(0.06)
· Trade	0.05	−0.06	0.00	0.02	−0.01
	(0.49)	(0.36)	(0.98)	(0.73)	(0.93)
· Productivity	**1.13**	−0.82	−0.41	**1.12**	0.22
	(0.04)	(0.15)	(0.73)	(0.05)	(0.84)
· CPI	**4.93**	2.31	−1.28	0.94	**1.05**
	(0.00)	(0.28)	(0.79)	(0.68)	(0.01)
· GDP	0.66	−3.77	−1.34	0.16	2.57
	(0.72)	(0.10)	(0.70)	(0.95)	(0.22)
· IP	−0.04	−0.01	0.21	−0.09	**1.57**
	(0.87)	(0.97)	(0.66)	(0.80)	(0.00)
· UEM	0.12	0.30	0.51	−0.80	−3.07
	(0.93)	(0.84)	(0.87)	(0.64)	(0.19)
· CExp	−0.84	−0.58	0.52	−1.26	0.04
	(0.41)	(0.57)	(0.85)	(0.51)	(0.98)
· GovC	**1.84**	−0.21	−1.74	−0.49	**−3.94**
	(0.09)	(0.81)	(0.32)	(0.71)	(0.02)

Notes: Variable explanation see text. Sample period 2004 to 2012 (388 Obs.). P-values in parentheses are adjusted for heteroscedasticity.

down US inflation expectations. In contrast, an unexpected increase in US consumer credit has the effect of a demand shock. It results in a positive $\varepsilon_{t,2}$ and an increase of inflation expectations.

The regressions indicates that the MS-SVAR model extracts some US ($\varepsilon_{t,2}$), EA ($\varepsilon_{t,1}$) and global ($\varepsilon_{t,5}$) macro shocks. The other two are insensitive to the macro shock instruments thus are candidates for expectations shocks.