**Supplementary material**

**A. Construction of the Credit Provision dataset – ECB Bank Lending Survey**

Note: The Table presents the detailed list of the questions used in this paper retrieved by ECB Bank Lending Survey (refer to <http://sdw.ecb.europa.eu/browse.do?node=9691151>). The methodology and the detailed questionnaire is updated in April 2015. For the purpose of our study, the column “Generated Field” includes the calculations we executed to quantify the Demand for Loans, Supply of Loans and Borrowers’ Quality.

| **Question in ECB BLS** | **Number** | **Construction** | **Definition** | **Generated Field** |
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| **Demand for Loans** |  |  |  |  |
| Over the past three months (apart from normal seasonal fluctuations), how has the demand for loans or credit lines to enterprises changed at your bank? | Q6 | Net percentage of banks reporting an increase of the demand for loans | Difference between the sum of banks answering “increased considerably” and “increased somewhat” and the sum of banks answering “decreased somewhat” and “decreased considerably” in percentage of the total number of banks | Average of sum percentages in Q6 and Q18 |
|  |  |  |  |
| Over the past three months (apart from normal seasonal fluctuations), how has the demand for loans to households changed at your bank? | Q18 | Net percentage of banks reporting an increase of the demand for loans | Difference between the sum of banks answering “increased considerably” and “increased somewhat” and the sum of banks answering “decreased somewhat” and “decreased considerably” in percentage of the total number of banks |
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| **Supply of Loans** |  |  |  |  |
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| Over the past three months, how have your bank’s credit standards as applied to the approval of loans or credit lines to enterprises changed? | Q1 | Net percentage of banks reporting a tightening of credit standards | Difference between the sum of banks answering “tightened considerably” and “tightened somewhat” and the sum of banks answering “eased somewhat” and “eased considerably” in percentage of the total number of banks. | Average of sum percentages in Q1 and Q10 |
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| Over the past three months, how have your bank’s credit standards as applied to the approval of loans to households changed? | Q10 | Net percentage of banks reporting a tightening of credit standards | Difference between the sum of banks answering “tightened considerably” and “tightened somewhat” and the sum of banks answering “eased somewhat” and “eased considerably” in percentage of the total number of banks. |
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| **Borrowers' Quality** |  |  |  |  |
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| Over the past three months, how have the following factors affected your bank’s credit standards as applied to the approval of loans or credit lines to enterprises? Perception of risk - General economic situation and outlook - Industry or firm-specific situation and outlook/borrower's creditworthiness - Risk related to the collateral demanded | Q2, C | Net percentage of banks reporting a tightening of credit standards | Difference between the sum of banks answering “tightened considerably” and “tightened somewhat” and the sum of banks answering “eased somewhat” and “eased considerably” in percentage of the total number of banks. | Average of sum percentages in Q2,C Q11,C and Q10 14,C |
|  |  |  |  |
| Over the past three months, how have the following factors affected your bank’s credit standards as applied to the approval of loans to households for house purchase? Perception of risk - General economic situation and outlook - Housing market prospects, including expected house price developments - Borrower’s creditworthiness | Q11, C | Net percentage of banks reporting a tightening of credit standards | Difference between the sum of banks answering “tightened considerably” and “tightened somewhat” and the sum of banks answering “eased somewhat” and “eased considerably” in percentage of the total number of banks. |
|  |  |  |  |
| Over the past three months, how have the following factors affected your bank’s credit standards as applied to the approval of consumer credit and other lending to households Perception of risk - General economic situation and outlook - Creditworthiness of consumers price developments - Risk on the collateral demanded | Q14, C | Net percentage of banks reporting a tightening of credit standards | Difference between the sum of banks answering “tightened considerably” and “tightened somewhat” and the sum of banks answering “eased somewhat” and “eased considerably” in percentage of the total number of banks. |

**B. Estimation of the T-VAR model**

The T-VAR is represented by the following equation:

where denote the constant terms, is the matrix of n endogenous variables, and are lag polynomial matrices, is the threshold variable, *d* is the time lag which is assumed to be known and is the threshold level. The time lag *d* typically denotes the delay of the threshold variable in determining the regimes. According to the literature, the threshold variable should be assumed to have a certain delay in determining the regimes to prevent potential problems of endogeneity between the identified shock and the regimes. We set the delay parameter equal to two.

We estimate the T-VAR depicted in (1) by performing a Gibbs algorithm to obtain the parameters , where *i=1,2,* depending on which regime the economy lies. We first sample the VAR parameters from a conditional posterior normal distribution. In addition, , which is the covariance matrix of the reduced form errors, is drawn from a conditional inverse-Wishart distribution. Then, we sample the threshold parameter by a using a Metropolis Hastings (MH) algorithm within the Gibbs algorithm. In particular:

The priors are set as follows: We set a dummy prior as discussed in Blake and Mumtaz (2012):

(2)

where , are the prior means for the coefficients on the first lags in the Minnesota prior, denote the standard deviation of the OLS residual obtained from individual auto-regressive models, and controls the overall tightness of the prior distribution around the random walk or white noise. The latter governs the relative importance of the prior beliefs with respect to the information contained in the data. For example, if , then the prior equals to posterior and the data do not influence the estimates. We *set*  following Banbura et al. (2010) who suggest that the overall tightness of this prior should be chosen in relation to the size of the VAR. To give an intuition on the structure of the priors in equation (2), the first block of dummies imposes prior beliefs on the autoregressive coefficients corresponding to the endogenous variables of the model. The second block implements the prior on the error covariance matrix while the third block reflects the intercept which is set to a very small number. Since the variables in our Τ-VAR have a unit root, we use the sum-of-coefficients approach to favor unit roots. We implement this by adding the following dummy observations:

(3)

where captures the average level of variable and is the hyperparameter which controls the degree of shrinkage. As goes to zero we approach the case of exact differences, while as goes to *,* the prior is implemented less tightly. We follow the relative literature by setting a loose prior with *τ=10λ.*

We use a Gibbs sampling algorithm to approximate the posterior distributions of the model parameters. According to Uhlig (2005), this approach offers a convenient method to estimate error bands for impulse responses. The details of the conditional distributions and the estimation algorithm are described next. The conditional posterior distribution of follows the normal distribution and is given by:

while the conditional posterior distribution of is given by the inverse Wishart distribution:

, (5)

where , , denotes the number of rows in , and with being the dummy observations that define the prior for the left and the right hand side of the TVAR respectively.

The Gibbs sampler cycles through the following steps. We begin by setting the priors as explained above. We also set an initial value for the threshold variable. Here we follow the literature (Blake and Mumtaz, 2012) by using the mean of the threshold variable. Next, we:

(i) Separate the data into two regimes. The first regime includes all observations such that . The second regime includes all observations such that

(ii) Sample the parameters in each regime for according to the conditional posterior distributions (4) and (5).

*(iii)* Apply aMetropolis Hastings random walk algorithm to sample the threshold value . This process goes as follows. We assume that the prior of follows the normal distribution with ; we use the mean of the threshold variable as and the variance of the series as . Then we draw a new value of the threshold from the random walk process: *=.* Afterwards, we compute the acceptance probability:

(6)

where is the likelihood of the parameters, as the product of the likelihoods in the two regimes. Accordingly, the log likelihood in each regime is defined as:

(7)

We then draw . If accept else retain .

(iv)Repeat steps (i) to (iii) 50,000 times, discarding the first 40,000 as burn-in. The last 10,000 iterations are used to form the empirical distribution of our parameters.

**C. Estimation of GIR**

For simplicity, let contain all the history of the system up to *t-*1 *()* and the parameters and hyperparamaters of the model . GIR for a given regime are defined as:

(8)

where is the vector that contains the responses of variables at horizon *k*, and is the shock of interest.

The following steps are separately employed for each regime. First (i), given a Gibbs draw, a sequence of initial values of the actual and contiguous lagged values of the endogenous variables is chosen, corresponding to a particular history falling under one of the two regimes. Then (ii), a random sample of shocks is drawn based on the variance-covariance matrix of the residuals of the estimated VAR model. For each sequence of shocks, (iii) a path of the evolution of endogenous variables is simulated conditional on , on the estimated coefficients for both regimes and using the shock process . Hence, the model is allowed to change regimes over the forecast horizon. The resulting sequence is denoted by . In the next step (iv), conditional on , on the estimated coefficients and using the same series of random shocks , we impose an extra structural shock, on . The resulting sequence provides another estimate for . Next, (v) steps (ii) to (iv) are repeated K=500 times. Then, (vi), take the means of the forecasts over *K* and calculate the difference between the means such that: . Having done this, (vii), repeat steps (ii) to (vi) for all Gibbs draws and all histories. The result of this step is the impulse response functions. Last, (viii), take the mean of the resulting impulse response functions from all Gibbs draws. The result is the ultimate GIR of the respective regime in the T-VAR model.

References:

Banbura M., D. Giannone, and L. Reichlin, 2010. Large Bayesian VARs. Journal of Applied Econometrics, 25, 71–92.

Blake A. and H. Mumtaz, 2012. [Applied Bayesian econometrics for central bankers](https://ideas.repec.org/b/ccb/tbooks/4.html). [Technical Books](https://ideas.repec.org/s/ccb/tbooks.html), Centre for Central Banking Studies, Bank of England.

Uhlig, H., 2005, What are the effects of monetary policy on output? Results from an agnostic identification procedure, Journal of Monetary Economics, 52, 381–419.