### An Introduction to Graphs in Dynare

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#### Abstract

This paper provides an introduction to the graphs displayed by Dynare in its stoch\_simul, rplot, estimation, shock\_decomposition, and identification-commands.

Keywords: Dynare 4, graphs, stoch\_simul, estimation, shock\_decomposition, identification.

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### List of Abbreviations

BVAR	Bayesian Vector Autoregression.
DSGE	Dynamics Stochastic General Equilbrium.
HPDI	Highest Posterior Density Interval.
IRF	Impulse Response Function.
LRE	Linear Rational Expectation.
MC MCMC ML MS	Monte Carlo. Monte Carlo Markov Chain. Maximum Likelihood. Markov Switching.
RMSE	Root Mean Squared Error.
SV SVD	Singular Value. Singular Value Decomposition.
VAR	Vector Autoregression.

## List of Symbols

- $\gamma$  vector of linear rational expectations model coefficients.
- m moment vector.
- $\theta$  generic parameter vector.
- au vector of model solution coefficients.

## 1 Graphs Produced by stoch\_simul



Figure 1: Orthogonalized shock to  $e_a$  - Impulse response functions (Impulse Response Function (IRF)) generated by stoch\_simul. The underlying shock can be seen from either the figure title in Matlab or the file name. The x-axis displays the time horizon, while the y-axis displays deviations from the deterministic steady state, either in absolute deviations for linearized models or in percentage deviations for loglinearized models. The model used for the present graph is only linearized. Thus, the impact response for y means that y decreases by about 0.08 units. Predetermined variables like the capital stock in the present example are displayed in Dynare's end of period notation. Thus, k reacts on impact, because it is the capital stock at the end of the period, which is chosen by today's investment, but only becomes productive tomorrow.

If there are correlated shocks, Dynare uses a Cholesky decomposition to orthogonalize the shocks. The ordering in the Cholesky decomposition depends on the declaration order of the exogenous variables in the var\_exo-statement. For more information, see http://www.dynare.org/phpBB3/viewtopic.php?f=1&t=2574. In case you want to simulate two simultaneous shocks, see http://www.dynare.org/phpBB3/viewtopic.php?f=1&t=2515



Figure 2: Spectral density of y – Spectral density plot generated by stoch\_simul if options\_.SpectralDensity.trigger = 1; has been set. The graphs are saved to the graphs-subfolder. Graphs display the univariate spectral density of the respective variable under consideration. The x-axis depicts the frequency, while the y-axis shows the power of this time-series at the respective frequency.



**Figure 3: Simulated Trajectory** – Plot of the simulated trajectory of endogenous variables that can be generated by using the **rplot**-command after **stoch\_simul** or **simul**. Graphs display the simulated series over the simulation horizon. When used with the default option **options\_.rplottype=0**, the command prints all simulated series in one figure. The graphs are saved in the graphs-subfolder.



Figure 4: Simulated Trajectory – Plot of the simulated trajectory that can be generated by using the rplot-command after stoch\_simul or simul. Graphs display the simulated series over the simulation horizon. When used with the option options\_.rplottype=1 (top figure), the command prints one figure for each variable to plot. With option options\_.rplottype=2 (bottom figure), the command prints all series into one figure, but with different subplots for each series. The graphs are saved in the graphs-subfolder.

### 2 Graphs Produced by estimation



Figure 5: Priors – Prior plot generated by the plot\_priors-option of the estimationcommand. The x-axis displays part of the support of the prior distribution, while the y-axis displays the corresponding density. Standard deviations of shocks are designated by SE\_, followed by the name of the shock, while observational errors are indicated by SE\_EOBS\_, followed by the name of the observable variables. Correlation between shocks and measurement errors are indicated by CC\_ and CC\_EOBS\_ followed again by the names of the shock or observables.



Figure 6: Mode check plots – Mode check plot generated by the mode\_check-option of the estimation-command. This figure allows for checking whether the mode-computation found the (local) mode. The x-axis of each panel displays an interval of parameter values centered around the estimated mode (horizontal magenta line), while the y-axis displays the corresponding value of the log-likelihood kernel shifted up or down by the prior value at the posterior mode (green line) and of the posterior likelihood function (blue line). Differences in the shape between the likelihood kernel and the posterior likelihood indicate the role of the prior in influencing the curvature of the likelihood. Big red dots indicate parameter values for which the model could not be solved due to e.g. violations of the Blanchard-Kahn conditions (indeterminacy or no bounded solution). In the current plot, one such point is obtained when the autocorrelation coefficient rho is set to 1. The labeling of standard deviations and correlations is the same as in Figure 5.



Figure 7: Monte Carlo Markov Chain (MCMC) univariate diagnostics (Brooks and Gelman, 1998) – Univariate convergence diagnostics generated by the estimationcommand if mh nblocks is larger than 1 and mh replic larger than 1000. It is stored in the Output-subfolder. The first column with the appended (Interval) shows the Brooks and Gelman (1998, Section 3) convergence diagnostics for the 80% interval. The blue line shows the 80% interval/quantile range based on the pooled draws from all sequences, while the red line shows the mean interval range based on the draws of the individual sequences. The second and third column with the appended  $(m^2)$  and  $(m^3)$  show an estimate of the same statistics for the second and third central moments, i.e. the squared and cubed absolute deviations from the pooled and the within-sample mean, respectively. If the chains have converged, the two lines should stabilize horizontally and should be close to each other. The depicted graphs are based on an increasing number of parameter draws. The step size is ceil((NumberOfDraws-1000)/100). The first data point is always computed on a window from draw 500 to draw 1000. The subsequent window *ii* ranges from from draw (1000+ii\*stepsize)/2 to draw (1000+ii\*stepsize)/2. The labeling of standard deviations and correlations is the same as in Figure 5.



**Figure 8:** Multivariate convergence diagnostic – Multivariate convergence diagnostics generated by the estimation-command if mh\_nblocks is larger than 1 and mh\_replic larger than 1000. It is stored in the Output-subfolder. This diagnostics is the same as the univariate one depicted in Figure 7, except for the statistics now being based on the range of the posterior likelihood function instead of the individual parameters. Thus, the posterior kernel is used to aggregate the parameters. Again, convergence is indicated by the two lines stabilizing and being close to each other. The window size is the same as in the univariate case (see Figure 7 for a description).



Figure 9: Priors and posteriors – Prior-posterior plot generated by the estimationcommand if  $mh_replic > 0$ . The x-axis displays part of the support of the prior distribution, while the y-axis displays the corresponding density. The grey line shows the prior density also shown in Figure 5, while the black line shows the density of the posterior distribution. The green horizontal line indicates the posterior mode. If the posterior looks like the prior, either your prior was a very accurate reflection of the information in the data or, more usually, the parameter under consideration is only weakly identified and the data does not provide much information to update the prior. The strength of identification can be checked using the identification-command. The labeling of standard deviations and correlations is the same as in Figure 5.



Figure 10: Orthogonalized shock to e\_a – Bayesian IRF plot generated by the bayesian\_irf-option of the estimation-command. It is stored in the Output-subfolder. Generally, these IRFs are similar to the ones displayed in Figure 1 and use the same orthogonalization scheme. The main difference is that the stoch\_simul-IRFs are computed at the calibrated parameter combination, while the Bayesian IRFs are the mean impulse responses (not to be confused with the IRFs at the mean). The gray shaded areas provide highest posterior density intervals (Highest Posterior Density Interval (HPDI)). If you want to compute classical IRFs after estimation, use stoch\_simul after estimation as the latter will set the parameters to the posterior mode/mean, depending on whether you use maximum likelihood or Bayesian estimation. More information can be found in Adjemian, Bastani, Juillard, Karamé, Mihoubi, Perendia, Pfeifer, Ratto, and Villemot (2011)



**Figure 11:** Smoothed variables – Smoothed variables plot generated by the filtered\_vars-option of the estimation-command. It is stored in the Output-subfolder. The black line depicts the mean estimate of the smoothed variables ("best guess for the endogenous variables given all observations"), derived from the Kalman smoother. The green lines represent the deciles of the smoother distribution.



Figure 12: Smoothed Shocks – Smoothed Shocks plot generated by the estimationcommand when either maximum likelihood estimation (Maximum Likelihood (ML)) is used or Bayesian estimation *without* the smoother-option. It is stored in the main folder. The black line depicts the estimate of the smoothed structural shocks ("best guess for the structural shocks given all observations"), derived from the Kalman smoother at the posterior mode (ML) or posterior mean (Bayesian estimation).



Figure 13: Historical and smoothed variables – Historical and smoothed variables plot generated by the estimation-command when either maximum likelihood estimation (ML) is used or Bayesian estimation without the smoother-option. It is stored in the main folder. The dotted black line depicts the actually observed data, while the red line depicts the estimate of the smoothed variable ("best guess for the observed variable given all observations"), derived from the Kalman smoother at the posterior mode (ML) or posterior mean (Bayesian estimation). In case of no measurement error, both series are identical. (@ Michel: what is the point of printing them then?)



Figure 14: Smoothed shocks – Smoothed shocks plot generated by the filtered\_varsoption of the estimation-command. It is stored in the Output-subfolder. The black line depicts the mean estimate of the smoothed structural shocks ("best guess for the structural shocks given all observations"), derived from the Kalman smoother. The green lines represent the deciles of the smoother distribution.



Figure 15: Updated Variables – Updated variables plot generated by the filtered\_varsoption of the estimation-command. It is stored in the Output-subfolder. The black line depicts the mean estimate of the filtered endogenous variables ("best guess for the endogenous variables at time t given information up to the current observations t"), derived from the Kalman filter. The green lines represent the deciles of the smoother distribution.



Figure 16: One step ahead forecast (filtered variables) – One step ahead forecast plot generated by the filtered\_vars-option of the estimation-command. It is stored in the Output-subfolder. The black line depicts the mean estimate of the one step ahead forecast of the endogenous variables ("best guess for the endogenous variables at time t + 1 given information up to the current observations t"), derived from the Kalman filter. The green lines represent the deciles of the one step ahead forecast distribution.



Figure 17: Forecasted variables (mean) – Mean forecast plot generated by the forecastoption of the estimation-command. It is stored in the Output-subfolder. The black line depicts the mean forecasts for the endogenous variables, starting at the last observation of the sample and going as many steps into the future as specified in the forecast-option. The green lines again depict the mean forecast deciles. The mean forecasts only take the parameter uncertainty into account, but omit the uncertainty about future shocks. Future shocks are averaged out/set to 0.



Figure 18: Forecasted variables (point) – Point forecast plot generated by the forecastoption of the estimation-command. It is stored in the Output-subfolder. The black line depicts the point forecasts for the endogenous variables, starting at the last observation of the sample and going as many steps into the future as specified in the forecast-option. The green lines again depict the point forecast deciles. In contrast to the mean forecasts, the points forecast not only take the parameter uncertainty into account, but also take into consideration the uncertainty about future shocks.



**Figure 19:** Forecasts – Forecast plot generated by the forecast-option of the estimationcommand when used for ML-estimation. It is stored in the graphs-subfolder. The middle lines depict the point forecasts for the endogenous variables, starting at the last observation of the sample and going as many steps into the future as specified in the forecast-option. This point forecast is obtained at the posterior mode (ML). The blue lines represent classical confidence intervals with coverage specified by conf\_sig. They are derived from the forecast error variance of the state space representation. The default coverage is 60% (see # 338).

![](_page_25_Figure_0.jpeg)

Figure 20: Trace plot for parameter alp (block number 2) – Trace plot generated by the trace\_plot-command after estimation. It is stored in the graphs-subfolder. The gray line shows the MC iterations encountered during the MC chain indicated in the figure title for the indicated parameter. The black line depicts the N-period moving average (default: N=200). The current plot, showing the deep parameter *alp*, was created using the command trace\_plot(options\_,M\_,estim\_params\_,'DeepParameter',2,'alp'). The first three arguments are mandatory and always the same. The fourth input argument designates the type of parameter to be plotted. It can take the values

- 'DeepParameter' for a deep structural parameter defined in the parameters-command
- 'StructuralShock' for the standard deviation or correlation of structural shocks (defined in Dynare's estimated\_params-block using the stderr or corr-commands on exogenous variables)
- 'MeasurementError' for the standard deviation or correlation of measurement errors (defined in Dynare's estimated\_params-block using the stderr or corr-commands on endogenous variables)

The fifth input argument takes an integer specifying the number of the Markov Chain for which you want to plot the draws. The sixth input argument provides the name of the parameter to be plotted/the name of the exogenous or endogenous variable for which to plot the standard deviation of the structural shock or measurement error. In case of a correlation that should be plotted, you have to specify the name of the second affected endogenous or exogenous variable as the seventh input argument. For example, to plot the correlation between the shocks  $e_m$  and  $e_a$ , use trace\_plot(options\_,M\_,estim\_params\_,'StructuralShock',2,'e\_m','e\_a')

![](_page_26_Figure_0.jpeg)

Figure 21: Autocorrelogram for correlation between structural shocks  $e_m$  and  $e_a$  (block number 2) – Autocorrelogram plot generated by the mh\_autocorrelation\_function-command after estimation. It is stored in the graphs-subfolder. The black bars indicate the *n*-th order autocorrelation of the parameter in the specified Markov Chain shown in the figure title. The horizontal axis shows the lag order *n*, while the vertical axis depicts the corresponding autocorrelation at lag *n*. At 0, the correlation is always 1. Ideally, we would like the draws from the posterior to be iid. The higher the autocorrelation the more inefficient the MCMC is due to the correlation making one additional draw from the MCMC less informative compared to the already present draws. If the autocorrelation is very high, you will need a lot of draws in your MCMC. The syntax for plotting is the same as for the trace\_plot-command in Figure 20. The present graph has been created using mh\_autocorrelation\_function(options\_,M\_,estim\_params\_,'StructuralShock',2,'e\_m','e\_a')

### 3 Graphs Produced by dsge\_var

![](_page_27_Figure_1.jpeg)

Figure 22: Orthogonalized shock to e\_ms – Bayesian IRF plot generated by the bayesian\_irf-option of the estimation-command if the dsge\_var-option is specified. It is stored in the Output-subfolder. The thick black dashed line in the middle is the median IRF of the Dynamics Stochastic General Equilbrium (DSGE) Vector Autoregression (VAR). The thin black dashed lines are the first and ninth posterior deciles of the DSGE-VAR's IRFs. The thick solid black line is the median posterior IRF of the DSGE model, while the shaded area covers the space between the first and ninth posterior deciles of the DSGE's IRFs (i.e. basically the content of Figure 10).

### 4 Graphs Produced by forecast

The **forecast**-command makes use of the same functions as the forecasts after maximum likelihood estimation. See Figure for a description.

### 5 Graphs Produced by shock\_decomposition

![](_page_29_Figure_1.jpeg)

Figure 23: Shock decomposition – Shock decomposition plot generated by the shock\_decomposition-command. It is stored in the main folder. The black line depicts the deviation of the smoothed value of the corresponding endogenous variable from its steady state at the specified parameter\_set. Note that this differs from Figure 11, where the steady state was added. By default, the parameter\_set is the posterior\_mean if Bayesian estimation has been used and the posterior\_mode otherwise. The colored bars correspond to the contribution of the the respective smoothed shocks to the deviation of the smoothed endogenous variable from its steady state, i.e. our "best guess" of which shocks lead to our "best guess" for our unobserved variables. "Initial values" in the graphs refers to the part of the deviations from steady state not explained by the smoothed shocks, but rather by the unknown initial value of the state variables. This influence of the starting values usually dies out relatively quickly.

#### 6 Graphs Produced by identification

![](_page_30_Figure_1.jpeg)

Figure 24: prior mean - Identification using info from observables – Identification strength-plot generated by the identification-command. It is stored in the identification subfolder. **Upper Panel:** the bar charts depict the identification strength of the parameters based on the Fischer information matrix normalized by either the parameter at the prior mean (blue bars) or by the standard deviation at the prior mean (red bars) (see formulas (11) and (??) in Ratto (2011)). The weighting with the prior standard deviation uses the prior uncertainty for weighting and is particularly useful for cases where the prior mean is 0. In this case the weighting with the prior mean would falsely signal an identification strength of 0. The Fisher information matrix is either computed analytically (Iskrev, 2011) or based on simulations. Which version has been used is indicated in the figure title. Intuitively, the bars represent the normalized curvature of the log likelihood function at the prior mean in the direction of the parameter. If the strength is 0 as is the case for theta in the rightmost diagram, the parameter is not identified as the likelihood function is flat in this direction. In contrast, the larger the absolute value of the bars, the stronger is the identification. Note that the graphs generally use a log-scale except for parameters that are unidentified, which are shown with a bar length of exactly 0, i.e. no bar at all.

![](_page_31_Figure_0.jpeg)

Figure 25: prior\_mean - Identification using info from observables – Identification strength-plot generated by the identification-command. It is stored in the identification subfolder. Lower Panel: This panel further decomposes the effect shown in the upper panel. A weak identification can be due to either other parameters linearly compensating/replacing the effect of a parameter (i.e. parameters having exactly the same effect on the likelihood) or the fact that the likelihood does not change at all with the respective parameter. This latter effect is called sensitivity (computed according to formula (12) in Ratto (2011)) and is plotted in the bottom panel. Again, weighting can take place either with the prior mean (blue bars) or the prior standard deviation (red bars). The bottom panel shows that the sensitivity of theta is 0. Thus, theta is not identified at the local mean, because it does not affect the likelihood and hence the model moments.

![](_page_32_Figure_0.jpeg)

Figure 26: prior\_mean - Sensitivity plot - Sensitivity-plot generated by the identification-command. It is stored in the identification subfolder. It shows an aggregate measure of how changes in the elements of the parameter vector  $\theta$  impact on the model moments. The "impact" is measured locally using the Jacobian, i.e. the local derivatives. The problem is that derivatives are not scale-invariant and thus not easily comparable. Hence, a normalization of the derivative of the *j*th moment of the moment vector,  $m_j$ , with respect to the parameter entry i,  $\partial m_i / \partial \theta_i$  is performed. This is done by multiplying with the ratio of standard deviations  $std(\theta_i)/std(m_i)$  (square root of formula (16) in Ratto (2011)). This normalization of the change in the parameter i,  $\partial \theta_i$ , by its variance,  $std(m_i)$ , accounts for different parameter uncertainty by ascribing ceteris paribus more importance to more variable parameters, because they will be responsible for higher changes in the moments (thereby effectively normalizing across parameters i). At the same time, the normalization of the change in the moment  $\partial m_i$  with its standard deviation,  $std(m_i)$ , allows for comparing the impact of parameter i on differently volatile moments (effectively normalizing across moments i). Thus, when taking the norm (i.e. length) of the columns of the standardized Jacobian, one ends up with a single aggregate sensitivity measure over all moments j for each parameter i. Dynare plots three different measures of sensitivity. The bars shown in the figure depict the norm of the columns of three different standardized Jacobian matrices for the respective parameter shown on the x-axis. The respective Jacobian matrices refer to i) the moments matrix  $(\partial m_T / \partial \theta')$ , indicting how well a parameter can be identified due the strength of its impact on the observed moments, ii) the model solution matrices  $(\partial \tau / \partial \theta')$ , indicating how well a parameter could in principle be identified if all state variables were observed, and iii) the Linear Rational Expectations (Linear Rational Expectation (LRE)) model  $(\partial \gamma / \partial \theta')$ , indicating trivial cases of non-identifiability due to e.g. some parameters always showing up as a product only in the model equations. (@MARCO: is it correct that e.g. for the LRE case, the Jacobian is of  $\gamma$  instead of  $m_T$ ? The manual is not explicit here.) If the moment matrix indicates non-identifiability and the model solution matrix indicates identifiability, it means that your observables in the var\_obs-command are not sufficient.

As the sensitivity is analyzed at the prior mean, this is a point estimate which uses analytic derivatives to compute the variance of the moments m.

![](_page_33_Figure_0.jpeg)

prior\_mean – Collinearity patterns with 2 parameter(s)

Figure 27: prior\_mean - Collinearity pattern with 2 parameter(s) – Collinearity pattern-plot generated by the identification-command. It is stored in the identification subfolder. The plot shows which linear combination of parameters shown in the columns best replicates/replaces the effect of the parameter depicted in the row on the moments of the observables. Higher values imply the relative redundancy and thus weak or un-identifiability of the parameter under consideration. This analysis is conducted via brute force. For each single parameter a set of regressions is run of the column of the Jacobian corresponding to the parameter in the row on all possible combinations of x other Jacobian columns  $(x \in \{1, \dots, \max \text{ dim cova group}\})$ . The aim is finding the column (and thus parameter) combination with the highest  $R^2$ . The resulting collinearity pattern between the parameter in the row and the set of parameters in the columns is then shown in the figure. Dynare generates plots for each set size of columns and thus parameters starting at 1 up to max dim cova group. The depicted plot shows an example for a set size of two. The darker red the squares are, the more critical is the collinearity between parameters. For example, the first row signifies that there is a strong correlation between the effect of  $e^{-a}$  on the model moments and the effect of *alp* and *psi*.

![](_page_34_Figure_0.jpeg)

Figure 28: prior\_mean - Identification patterns (Information matrix): SMALL-EST SV – Identification pattern-plot generated by the identification-command. It is stored in the identification subfolder. Following Andrle (2010), the parameter groups with the strongest and weakest identification can be identified from the singular value decomposition (Singular Value Decomposition (SVD)) of the Fischer information matrix. This graph shows the smallest singular values (Singular Value (SV)) and the associated eigenvectors of parameters. The parameter combinations associated with the smallest singular values are closest to being perfectly collinear and thus redundant. A singular value of 0, as is the case for theta, implies that the parameter is completely unidentified as it is responsible for the information matrix being rank deficient due to the parameter having no effect at all on the likelihood.

![](_page_35_Figure_0.jpeg)

Figure 29: prior\_mean - Identification patterns (Information matrix): HIGHEST SV –Identification pattern-plot generated by the identification-command. It is stored in the identification subfolder. This graph shows the largest singular values and the associated eigenvectors of parameters. It has the same interpretation as the graph for the smallest singular values, Figure 28, except for now depicting the parameters being most uncorrelated and thus best identified.

![](_page_36_Figure_0.jpeg)

Figure 30: MC sensitivities – Collinearity pattern-plot generated by the identificationcommand. It is stored in the identification subfolder. It shows an aggregate measure of how changes in the elements of the parameter vector  $\theta$  impact on the model moments. The interpretation of the graphs is the same as for the prior mean sensitivities depicted in Figure 26, except for the measure now being not a point estimate but being averaged over the Monte Carlo (Monte Carlo (MC)) sample of the parameters  $\theta$ , thus providing a description of sensitivity over the whole parameter space.

![](_page_37_Figure_0.jpeg)

log10 of Condition number in the moments  $\begin{array}{c}
80\\
60\\
40\\
20\\
0\\
2 \\
2.5 \\
3 \\
3.5 \\
4
\end{array}$ 

Figure 31: MC condition number – Condition number-plot generated by the identification-command. Requires the advanced and prior\_mc-options. It is stored in the identification subfolder. It depicts the condition numbers of the Jacobians of the model moments  $(\partial m_T / \partial \theta', \text{ first plot})$ , the model solution matrices  $(\partial \tau / \partial \theta', \text{ second plot})$ , and the LRE model  $(\partial \gamma / \partial \theta', \text{ third plot})$  encountered during the MC simulations. A large condition number signals near-singularity of the respective Jacobian and thus weak identifiability. Hence, the plot provides an overview about the occurrence of identification problems over the whole parameter range as encountered during MC simulations.

![](_page_38_Figure_0.jpeg)

Figure 32: MC condition number – Condition number-plot generated by the identification-command. Requires the advanced and prior\_mc-options. It is stored in the identification subfolder. This plot uses the condition number of the Jacobian to trace out which parameters are only weakly identified and thus responsible for the Jacobian being close to singular. To do so, the parameters encountered during MC are split into two samples, depending on whether they occurred in a draw with a condition number above the median or not. Testing whether the parameter distributions in both samples significantly differ, provides an indication whether the parameter under consideration is the source of the Jacobian being close to singular.

The dotted line represents the cumulative distribution of parameter values associated with condition numbers in the bottom half, while the solid line depicts the cumulative distribution associated with condition numbers in the upper half. The p-value above each subplot indicates the probability of both distributions being equal according to a Smirnov test (see Ratto (2008) for details about this procedure and its foundation in Monte Carlo Filtering). Generally, only parameters with p-value below 0.1 are plotted in Dynare.

Dynare generates three plots corresponding to the condition numbers of the Jacobians of the model moments  $(\partial m_T / \partial \theta', \text{ first plot})$ , the model solution matrices  $(\partial \tau / \partial \theta', \text{ second plot})$ , and the LRE model  $(\partial \gamma / \partial \theta', \text{ third plot})$  encountered during the MC simulations. These figures are only saved to the disk, but not displayed after the run of identification.

![](_page_39_Figure_0.jpeg)

Figure 33: MC Sample - MC identification patterns (moments): SMALLEST SV – Identification pattern-plot generated by the identification-command. Requires the advanced and prior\_mc-options. It is stored in the identification subfolder. It shows the distribution of the parameter vectors associated with the smallest singular value of the Jacobian (see Figure 28 for a description for the case of the information matrix) during the MC runs. Note that in contrast to Figure 28 the SVD applies to the Jacobian of the moments m with respect to the parameters  $\theta$ , not the Fischer information matrix. This also explains the large differences in the scale of the singular values.

The blue bars depict the mean value, while the red starred lines represent the 90% quantiles. If the quantiles are narrow or one quantile is close to the mean, it suggests that the identification pattern is similar over the whole parameter space. This can be clearly seen for theta, which is unidentified over the whole sample. Similarly, for the second smallest singular value, the mean of rho is identical to the upper 90% bound, while the other means are close to the lower bound. This suggests that psi is weakly identified over the whole parameter space and that the weak identification is not due to collinearity with other parameters. This evidence is consistent with second panel of Figure 28.

![](_page_40_Figure_0.jpeg)

Figure 34: MC Sample - MC identification patterns (moments): HIGHEST SV - Identification pattern-plot generated by the identification-command. Requires the advanced and prior\_mc-options. It is stored in the identification subfolder. It shows the distribution of the parameter vectors associated with the largest singular value of the Jacobian of the moments (see Figures 29 and 33) during the MC runs. This figure is similar to Figure 33, except for showing the parameter combinations with the strongest identification.

#### 7 Graphs Produced by dynare\_sensitivity

![](_page_41_Figure_1.jpeg)

Figure 35: Prior StabMap: Parameter driving non-existence of unique stable solution (Unacceptable) – Prior stability mapping plot generated by the dynare\_sensitivitycommand. This figure analyzes which parameters are responsible for not finding a unique and stable solution to the model (i.e. where the Blanchard-Kahn conditions are not satisfied, or the steady state could be computed, or NaN or Inf appear in the derivatives or model solution). To do so, the parameters encountered during MC draws from the prior distribution are split into two samples, depending on whether they occurred in a draw where a unique and stable solution could be found or not. Testing whether the parameter distributions in both samples significantly differ, provides an indication whether the parameter under consideration is the source of the model solution not existing.

The dotted line represents the cumulative distribution of parameter values associated with a unique and stable solution, while the solid line depicts the cumulative distribution associated with a failure to compute a unique stable solution. The p-value above each subplot indicates the probability of both distributions being equal according to a Smirnov test (see Ratto (2008) for details about this procedure and its foundation in Monte Carlo Filtering). Generally, only parameters with p-value below 0.1 are plotted in Dynare.

In the present example, both the discount factor *beta*, if it becomes larger than 1, and the autocorrelation parameter *rho*, if its absolute value is bigger than 1, drive the non-existence of a solution. The subsequent graphs show that *beta*>1 leads to the non-existence of a steady state, while |rho|>1 leads to a violation of the BK-condition.

The plot is also available for the posterior instead of the prior draws. It is stored in the gsa subfolder.

![](_page_42_Figure_0.jpeg)

Figure 36: Prior StabMap: Parameter driving explosiveness of solution – Prior stability mapping plot generated by stability mapping of the dynare\_sensitivity-command. This analyzes which parameters are responsible for finding an explosive solution to the model, i.e. where the Blanchard-Kahn conditions are violated due to the existence of more eigenvalues outside of the unit circle than forward looking variables. To do so, the parameters encountered during MC draws from the prior distribution are split into two samples, depending on whether they occurred in a draw where an explosive solution was found or not. Testing whether the parameter distributions in both samples significantly differ, provides an indication whether the parameter under consideration is the source of the model solution exploding.

The dotted line represents the cumulative distribution of parameter values associated with a unique and stable solution, while the solid line depicts the cumulative distribution associated with an explosive solution. The p-value above each subplot indicates the probability of both distributions being equal according to a Smirnov test (see Ratto (2008) for details about this procedure and its foundation in Monte Carlo Filtering). Generally, only parameters with p-value below 0.1 are plotted in Dynare.

The plot is also available for the posterior instead of the prior draws. It is stored in the gsa subfolder.

![](_page_43_Figure_0.jpeg)

Figure 37: Prior StabMap: Parameter driving inability to find solution – Prior stability mapping plot generated by stability mapping of the dynare\_sensitivity-command. This analyzes which parameters are responsible for Dynare being unable to compute a solution to the model. Reasons are for example the inability to compute a steady state or the appearance of NaN or Inf in the derivatives or model solution (violations of the Blanchard-Kahn conditions are not counted). To do so, the parameters encountered during MC draws from the prior distribution are split into two samples, depending on whether they occurred in a draw where a solution could be computed or not. Testing whether the parameter distributions in both samples significantly differ, provides an indication whether the parameter under consideration is the source of the model solution exploding.

The dotted line represents the cumulative distribution of parameter values where a solution could be computed, while the solid line depicts the cumulative distribution associated with the inability to compute a solution. The p-value above each subplot indicates the probability of both distributions being equal according to a Smirnov test (see Ratto (2008) for details about this procedure and its foundation in Monte Carlo Filtering). Generally, only parameters with p-value below 0.1 are plotted in Dynare.

In the present example, if the discount factor *beta* is larger than 1 no steady state can be computed, thus driving the inability to compute a solution.

The plot is also available for the posterior instead of the prior draws. It is stored in the gsa subfolder.

TBA: Stab\_map\_2-Graphs @Marco: Do you have an easy example that generates those?

![](_page_45_Figure_0.jpeg)

Figure 38: Reduced Form Mapping - Reduced form mapping plot generated by the redform-option of the dynare\_sensitivity-command. (@Marco: What does redform do? Interpretation of the graph?) Graphs of this type are created for all combinations of specified endogenous variables with exogenous and lagged endogenous variables. The graphs are stored in the gsa\reform\_stab subfolder in a folder designating the name of the variable combination.

![](_page_46_Figure_0.jpeg)

Figure 39: Reduced Form Mapping (Threshold) - Reduced form mapping plot generated by the redform-option of the dynare\_sensitivity-command. (@Marco: What does redform do? Interpretation of the graph?) Graphs of this type are created for all combinations of specified endogenous variables with exogenous and lagged endogenous variables, provided any p-value is above the significance threshold. The graphs are stored in the gsa\reform\_stab subfolder in a folder designating the name of the variable combination.

![](_page_47_Figure_0.jpeg)

**Figure 40: RMSE Prior: Log Prior** – Root mean squared error (Root Mean Squared Error (RMSE)) plot generated by RMSE-option of the dynare\_sensitivity-command. (@Marco: What does RMSE do? Interpretation of the graph?), Similar graphs exist for the Posterior and MC instead of the prior distribution. It is stored in the gsa subfolder.

![](_page_48_Figure_0.jpeg)

**Figure 41: RMSE Prior: Log Likelihood** – RMSE plot generated by RMSE-option of the dynare\_sensitivity-command. (@Marco: What does RMSE do? Interpretation of the graph?), Similar graphs exist for the Posterior and MC instead of the prior distribution. It is stored in the gsa subfolder.

![](_page_49_Figure_0.jpeg)

**Figure 42: RMSE Prior: Log Posterior** – RMSE plot generated by RMSE-option of the dynare\_sensitivity-command. (@Marco: What does RMSE do? Interpretation of the graph?), Similar graphs exist for the Posterior and MC instead of the prior distribution. It is stored in the gsa subfolder.

### 8 Graphs Produced by bvar\_forecast

![](_page_50_Figure_1.jpeg)

Figure 43: BVAR forecasts (nlags=8) – BVAR forecasts plot generated by the bvar\_forecast-command. It is stored in the graphs-subfolder. The blue line in the middle is the median forecast of the Bayesian Vector Autoregression (BVAR) in the absence of shocks, i.e. given only parameter uncertainty. The area between the green lines covers the options\_.conf\_sig percent HPDI interval (default: 60%) of the forecasts given only parameter uncertainty are uncertainty. The area between the red lines covers the options\_.conf\_sig percent HPDI interval (default: 60%) of the forecasts given both parameter uncertainty and uncertainty about future shock realization.

### 9 Graphs Produced by forecast

The graphs generated by the forecast-command are the same as for the forecast-option of the estimation command with Maximum Likelihood-estimation shown in Figure 4.

![](_page_52_Figure_0.jpeg)

10 Graphs Produced by conditional\_forecast

**Figure 44: Conditional forecast (Posterior Mode): gp\_obs** – Conditional forecast plot generated by the conditional\_forecast-command. It is stored in the graphs-subfolder. The solid black line is the mean conditional forecast. The grey area around the black solid line covers the options\_.conf\_sig percent confidence interval (default: 80%), computed as the corresponding percentiles of the forecasts. The dashed black line is the mean unconditional forecast. The area between the thin black dashed lines covers the options\_.conf\_sig percent confidence interval (default: 80%) of the unconditional forecasts, computed as the corresponding percentiles of the forecasts.

11 Graphs Produced by the Markov Switching VAR Codes

![](_page_53_Figure_1.jpeg)

Figure 45: MS-Probabilities, Chain 1 – Markov Switching (MS) probabilities plot generated by the ms\_compute\_probabilities-command. It is stored in the Output/Probabilities-subfolder. The x-axis shows the number of time periods and the y-axis the probabilities of the corresponding regimes. The title shows the number of the corresponding Markov Chain (with the total number set by the chain-option) for which the probabilities are displayed. By default, the probabilities are smoothed probabilities, i.e. using information up to time T. Using the filtered\_probabilities-option of the ms\_compute\_probabilities, filtered probabilities using only information up to time t can be requested.

![](_page_54_Figure_0.jpeg)

Figure 46: Impulse Response Ergodic – Impulse response function plot generated by the ms\_irf-command. It is stored in the Output/IRF-subfolder. The x-axis shows the number of time periods and the y-axis the deviation from the unconditional mean. The middle line shows the median IRF, while the upper and lower blue line depict the percentiles of the IRF distribution. They can be set using the error\_band\_percentiles-command and are 16% and 84% percentiles by default.

![](_page_55_Figure_0.jpeg)

**Figure 47: Forecast** – Forecast plot generated by the ms\_forecast-command. It is stored in the Output/Forecast-subfolder. The x-axis shows the number of time periods and the y-axis the forecasted deviation from the unconditional mean. The thick blue line is the mean of median forecast, with the two thin blue lines indicating the upper and lower percentiles of the forecast distribution. The percentiles are set in options\_.ms.percentiles and are 16% and 84% by default. The panel title shows the name of the respective variable.

![](_page_56_Figure_0.jpeg)

**Figure 48: Variance Decomposition Ergodic** – Forecast Error Variance Decomposition plot generated by the ms\_variance\_decomposition-command. It is stored in the Output/Variance\_Decomposition-subfolder. The x-axis shows the forecast horizon and the stacked colored columns the contribution of the corresponding shock to the overall forecast error variance at the respective horizon. The title shows the name of the variable for which the forecast error variance decomposition is performed.

### 12 Error Messages

POSTERIOR KERNEL OPTIMIZATION PROBLEM! (minus) the hessian matrix at the "mode" is not positive definite! => posterior variance of the estimated parameters are not positive. You should try to change the initial values of the parameters...

ERROR: final.mod:201.1-3: syntax error, unexpected NAME

The reason usually is that a semicolon is missing in the previous line, but people only look in the current line. If the error starts at 1, we might want to change the error message to

#### References

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