Estimation of a TVP-VAR with MSV via Efficient Importance Sampling

Project Proposal

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Motivation

Using VAR models to describe macroeconomic relations

"It should be feasible to estimate large-scale macromodels as unrestricted reduced forms, treating all variables as endogenous."

Christopher Sims, Macroeconomics and Reality (1980).

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- RBC models x **VAR approach**

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- RBC models x **VAR approach**
- Strong evidence of parameter instability in macroeconomic series: [Sims, 1999], [Bernanke and Mihov, 1998a], [Bernanke and Mihov, 1998b], [Mumtaz and Zanetti, 2015], [Galí and Gambetti, 2015], [Mumtaz and Theophilopoulou, 2015], [Mumtaz and Theophilopoulou, 2017], **[Cogley and Sargent, 2001], [Cogley and Sargent, 2005]**, etc.

Motivation

Cogley and Sargent (2005)

WHAT EXPLAINS THE WORSENING IN US INFLATION-UNEMPLOYMENT OUTCOMES IN 1970S?

Bad Luck vs Bad Policy

Based on Cogley and Sargent, 2005.

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Bad Luck vs **Bad Policy**

Changes in the inflation persistence

Changes in monetary policy rules

Changes in volatility structure

Bad luck:

It was not monetary strategy but increase/decrease of the shocks' volatility

Drifting coefficients

Bad policy:

The FED's view negates the natural rate theory and believes in an exploitable trade-off between unemployment and inflation

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Phillipov and Glickman (2006a, 2006b)

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Estimation of a TVP-VAR with MSV via EIS

Literature Review: TVP-VAR w/ MSV

Consider the following state-space representation of a TVP-VAR with MSV:

$$y_t = Z_t \alpha_t + \epsilon_t \qquad \epsilon_t \sim \mathcal{N}_k(0_k, \Omega_t^{-1}) \qquad \text{(measure eq.)} \qquad (1)$$

$$\alpha_t = \alpha_{t-1} + \upsilon_t \qquad \upsilon_t \sim \mathcal{N}_p(0_p, Q) \qquad \text{(state transition eq.)} \qquad (2)$$

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- If Ω_t^{-1} were non-stochastic, the Kalman Filter could be used to obtain the ML function;
  - Since it is not the case, we have an **analytically intractable high-dimensional integral**.

Estimation of a TVP-VAR with MSV via EIS

Literature Review: Cogley and Sargent (2001, 2005)

Their first work was a TVP-VAR of the form:

$$
\begin{aligned}
y_t &= Z_t\alpha_t + \epsilon_t \qquad \epsilon_t \sim \mathcal{N}_k(0_k, R) \qquad (3)\\
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After being criticized in (2001) for the lack of MVS in their model, [Cogley and Sargent, 2005] proposed changing ϵ_t in (3) for $\epsilon_t = {R_t}^{1/2}\xi_t$, where ξ_t follows a standard normal distribution and $R_t = B^{-1}H_tB^{-1\prime}$ with:

$$B = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \beta_{21} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{k1} & \beta_{k2} & \cdots & 1 \end{bmatrix}, \quad \text{and} \quad H_t = \begin{bmatrix} h_{1t} & 0 & \cdots & 0 \\ 0 & h_{2t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & h_{kt} \end{bmatrix}$$

$$\text{where} \quad ln(h_{it}) = ln(h_{it-1}) + \sigma_i\eta_{it}, \quad \eta_{it} \sim \mathcal{N}(0,1).$$

Estimation of a TVP-VAR with MSV via EIS

Literature Review: Primiceri (2005)

[Primiceri, 2005] proposed the same specification as [Cogley and Sargent, 2005] but allowed the covariances in B to evolve over time:

$$B_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \beta_{21,t} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{k1,t} & \beta_{k2,t} & \cdots & 1 \end{bmatrix} \quad \text{with} \quad \beta_t = \beta_{t-1} + \upsilon_t \tag{5}$$

where υ_t are mean-zero normal errors with constant covariance matrix.

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Drawback: (5) is not invariant to the observable variables y_t order!

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The problem lies in the MSV structure!

Estimation of a TVP-VAR with MSV via EIS

Literature Review: Phillipov and Glickman (2006a, 2006b)

[Philipov and Glickman, 2006b] and [Philipov and Glickman, 2006a] proposes the following model:

$$y_t = \epsilon_t, \qquad \epsilon \sim \mathcal{N}_k(0_k, \Omega_t^{-1}) \tag{6}$$

$$\Omega_t | \Omega_{t-1} \sim \mathcal{W}(\nu, S_{t-1}), \qquad \text{with } S_t = \frac{1}{\nu} A^{1/2} \Omega_t^{d} A^{1/2\prime} \tag{7}$$

where

- A is a positive definite symmetric matrix containing parameters determining the intertemporal sensitivity of each element of the precision matrix and
- $d \in [0, 1)$ is a scalar that accounts for overall persistence of the process.

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where

- A is a positive definite symmetric matrix containing parameters determining the intertemporal sensitivity of each element of the precision matrix and
- $d \in [0, 1)$ is a scalar that accounts for overall persistence of the process.

This specification is more flexible than Primiceri's one, and it is invariant to ordering!

Estimation of a TVP-VAR with MSV via EIS

Literature Review: Phillipov and Glickman (2006a, 2006b)

- [Philipov and Glickman, 2006a] had trouble estimating simultaneously the elements of the matrix A and persistence parameter *d* and proposed to use a fixed *d*;

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- [Philipov and Glickman, 2006a] had trouble estimating simultaneously the elements of the matrix A and persistence parameter d and proposed to use a fixed d;
- [Asai and McAleer, 2009] reported convergence problems in the Gibbs sampler.

Estimation of a TVP-VAR with MSV via EIS

Where are we?

Philipov and

Primiceri (2005)

- The order of the variables y_t matters;
- Simple random walk structure for covariances;
- Missing steps in Gibbs sampler.

Estimation problems

Estimation of a TVP-VAR with MSV via EIS

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- MVS specification
- Invariant to the order in y_t ;
- Flexible autoregressive structure for covariances;
- Almost same number of parameters.

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Estimation of a TVP-VAR with MSV via EIS

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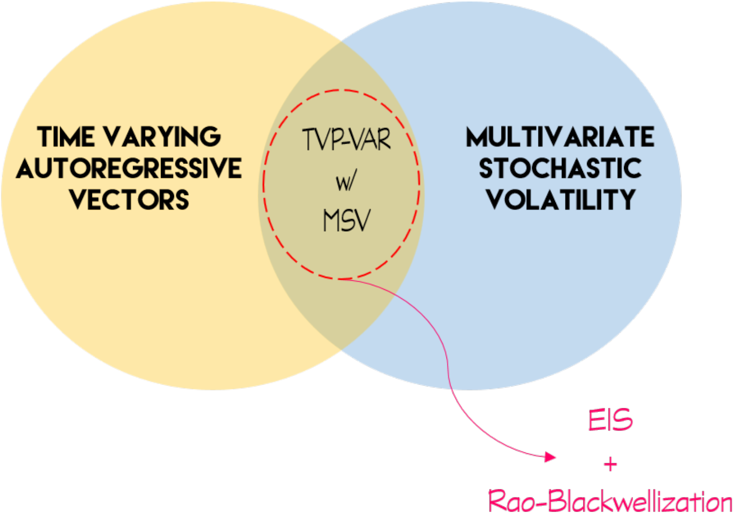
Estimation of a TVP-VAR with MSV via EIS

Objective

Develop and implement efficient statistical inference procedures in TVP-VAR with MSV models.

Estimation of a TVP-VAR with MSV via EIS

Proposal



Estimation of a TVP-VAR with MSV via EIS

Proposal

Build a **TVP-VAR** with **Wishart MSV** model based on [Philipov and Glickman, 2006b] and obtain **maximum likelihood** estimates using **EIS** [Richard and Zhang, 2007] combined with a **Rao-Blackellization** step [Moura and Turatti, 2014].

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Specific Objectives:

1. Obtain the ML estimates for the MSV Wishart model from [Philipov and Glickman, 2006b] using EIS as well develop diagnostic tools to study numerical properties;

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1. Obtain the ML estimates for the MSV Wishart model from [Philipov and Glickman, 2006b] using EIS as well develop diagnostic tools to study numerical properties;
2. Generalize the previous model to a TVP-VAR with drifting coefficients plus MSV and implement EIS algorithm combined with a Rao-Blackwellization step, as well as develop diagnostic tools;

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2. Generalize the previous model to a TVP-VAR with drifting coefficients plus MSV and implement EIS algorithm combined with a Rao-Blackwellization step, as well as develop diagnostic tools;
3. Develop an empirical application using the model developed in (2), in line with [Mumtaz and Theophilopoulou, 2017].

- Monte Carlo (MC) Methods are an alternative way to solve complex integrals;
    - Specially used for high-dimension problems, where non-stochastic algorithms are way too slow;
- The idea is to resample values from a probability density (thus, is a stochastic method), using a pseudo-random number generator and the inverting theorem.

Consider the following integral:

$$I = \int_{\chi} g(x) f(x) dx \tag{8}$$

Estimation of a TVP-VAR with MSV via EIS

Methodology: Monte Carlo Methods and Importance Sampling

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If X is a random vector with pfd $f_X(\cdot)$, then (8) is the expectation of $g(X)$ with respect to $f(\cdot)$:

$$I = \mathbb{E}_f[g(x)] \tag{9}$$

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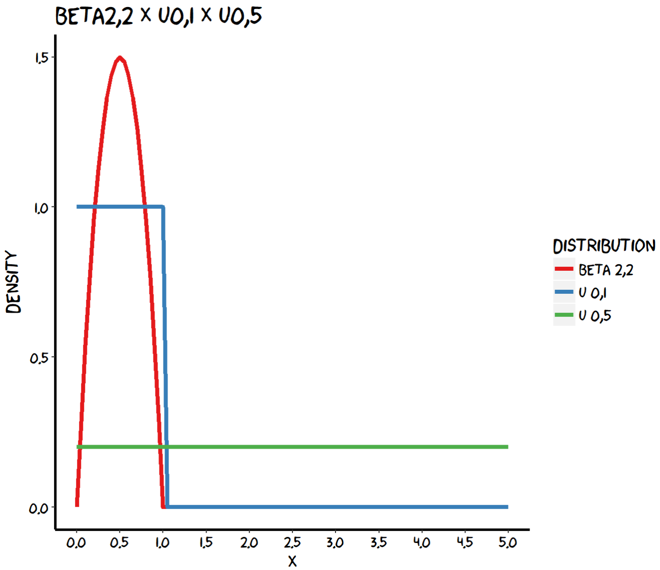
In cases where the function f is known, using the law of large numbers we can use the sample mean to approximate (8):

$$I \approx \frac{1}{N} \sum_{i=1}^{N} g(x_i) \tag{10}$$

Estimation of a TVP-VAR with MSV via EIS

Methodology: Monte Carlo Methods and Importance Sampling



Estimation of a TVP-VAR with MSV via EIS

Methodology: Monte Carlo Methods and Importance Sampling

Consider the following integral:

$$I = \int_{\chi} g(x) \frac{f(x)}{m(x)} m(x) dx \tag{11}$$

Now we have an expectation with respect to the density $m(\cdot)$:

$$I = \mathbb{E}_m \left[\frac{g(x) f(x)}{m(x)} \right] \tag{12}$$

In cases where the function m is known, using the law of large numbers we can use the sample mean to approximate (11):

$$I \approx I_N^{IS} = \frac{1}{N} \sum_{i=1}^{N} \omega(x_i) g(x_i), \qquad \text{with} \quad \omega_i = \frac{f(x_i)}{m(x_i)} \tag{13}$$

Estimation of a TVP-VAR with MSV via EIS

Methodology: Efficient Importance Sampling

Two main "problems" arise when dealing with IS:

- The choice of the class of samplers, *M*;

Estimation of a TVP-VAR with MSV via EIS

Methodology: Efficient Importance Sampling

Two main "problems" arise when dealing with IS:

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- The selection of a sampler in M that minimizes the Monte Carlo variance.

Estimation of a TVP-VAR with MSV via EIS

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  $\Rightarrow$ EIS resolves the last one!

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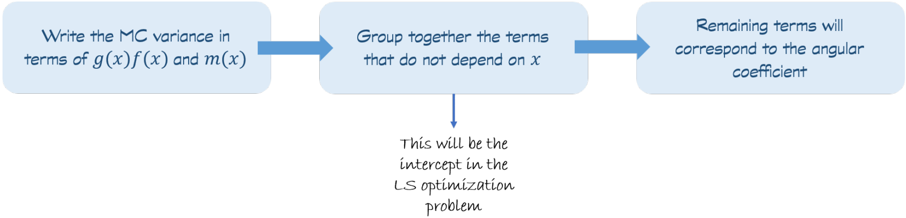

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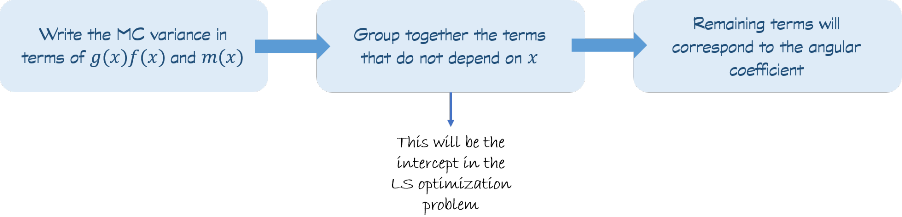
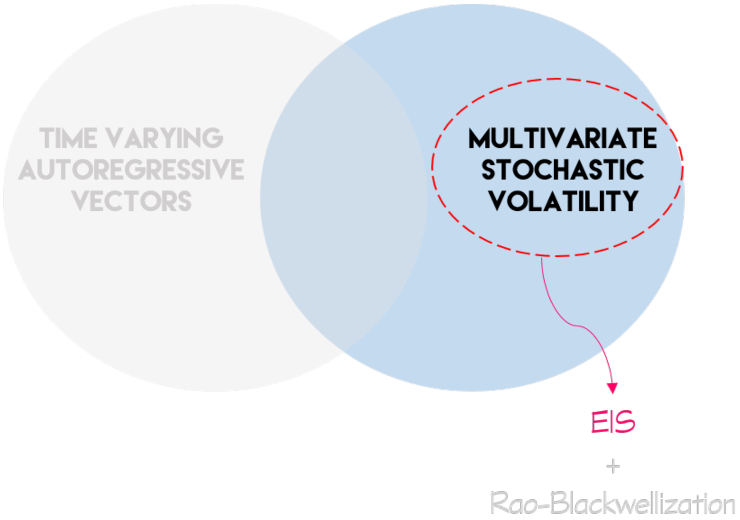


- Sequential EIS is used in high-dimensional problems and consists in "breaking" the EIS algorithm in a sequence of low-dimension optimizations.

Estimation of a TVP-VAR with MSV via EIS

Methodology: Wishart MSV model



Estimation of a TVP-VAR with MSV via EIS

Methodology: Wishart MSV model

Recall the model given in (6)-(7). Defining $f(\underline{y}, \underline{\Omega}, \theta)$ as the joint density of $\underline{y} = \{y_t\}_{t=1}^{T}$ and $\underline{\Omega} = \{\Omega_t\}_{t=1}^{T}$, where θ is the vector of unknown parameters, the likelihood associated to $\underline{y}_t$ is given by:

$$\begin{aligned} L(\theta|\underline{y}) &= \int f(\underline{y}.\underline{\Omega}, \theta) d\underline{\Omega} \\ &= \int \cdots \int \prod_{t=1}^{T} f(y_t, \Omega_t | \underline{\Omega}_{t-1}, \underline{y}_{t-1}; \theta) d\Omega_1 \ldots d\Omega_T \end{aligned} \tag{14}$$

with $\underline{y}_t$ e $\underline{\Omega}_t$ given by $\{y_t\}_{t=1}^{T}$ e $\{\Omega_t\}_{t=1}^{T}$, respectively.

Estimation of a TVP-VAR with MSV via EIS

Methodology: Wishart MSV model

The respective space-state representation is:

$$f(y_t, \Omega_t | \underline{\Omega}_{t-1}, \underline{y}_{t-1}; \theta) = g(y_t | \Omega_t, \underline{y}_{t-1}; \theta) \cdot p(\Omega_t | \underline{\Omega}_{t-1}, \underline{y}_{t-1}; \theta) \tag{15}$$

where

$$g(y_t | \Omega_t, \underline{y}_{t-1}; \theta) \propto |\Omega_t|^{1/2} \exp\left\{-\frac{1}{2} y_t' \Omega_t y_t\right\} \tag{16}$$

$$p(\Omega_t | \underline{\Omega}_{t-1}, \underline{y}_{t-1}; \theta) \propto |\Omega_t|^{\frac{\nu-k-1}{2}} \exp\left\{-\frac{1}{2} tr\left[S_{t-1}^{-1} \cdot \Omega_t\right]\right\} \tag{17}$$

Estimation of a TVP-VAR with MSV via EIS

Methodology: Wishart MSV model

Likelihood:

$$L(\theta|\underline{y}) = \int \prod_{t=1}^{T} \left[\frac{f(y_t, \Omega_t|\underline{\Omega}_{t-1}, \underline{y}_{t-1}; \theta)}{m(\Omega_t|\underline{\Omega}_{t-1;\gamma_t})} \right] \prod_{t=1}^{T} m(\Omega_t|\underline{\Omega}_{t-1;\gamma_t}) d\underline{\Omega} \tag{18}$$

with $m(\Omega_t|\underline{\Omega}_{t-1;\gamma_t}) = \frac{k(\underline{\Omega}_t;\gamma_t)}{\chi(\underline{\Omega}_{t-1};\gamma_t)}$ where $\chi(\underline{\Omega}_{t-1}; \gamma_t) = \int k(\underline{\Omega}_{t-1}; \gamma_t) d\Omega_t$.

MC estimate:

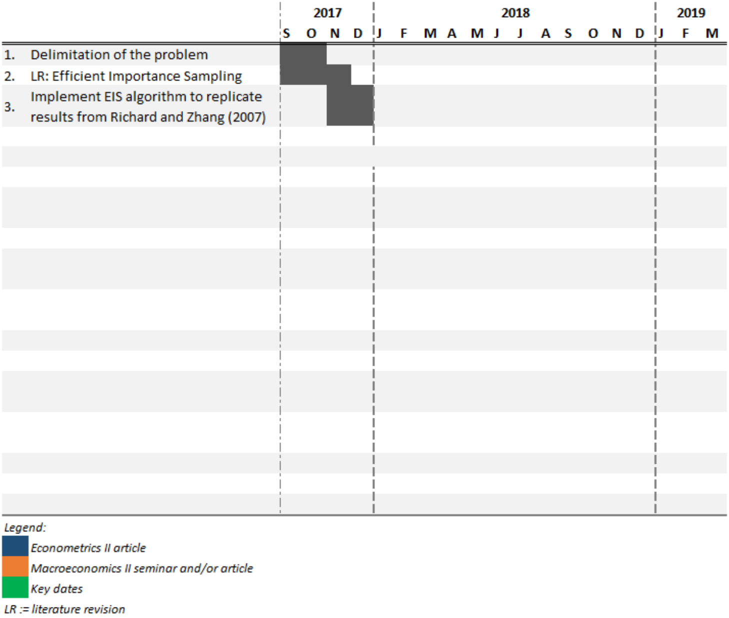
$$\tilde{L}(\theta|\underline{y}) = \frac{1}{N} \sum_{i=1}^{N} \left[\prod_{\ell=1}^{L} \frac{f(y_t, \tilde{\Omega}_t^i|\tilde{\underline{\Omega}}_{t-1}^i, \underline{y}_{t-1}; \theta) \cdot \chi(\tilde{\underline{\Omega}}_{t-1}^i; \gamma_t)}{k(\tilde{\underline{\Omega}}_t^i; \gamma_t)} \right] \tag{19}$$

Minimization problem:

$$\hat{\gamma}_t(\theta) = \min_{\gamma_t} \sum_{i=1}^{N} \left\{ \ln \left[f(y_t, \tilde{\Omega}_t^i|\tilde{\underline{\Omega}}_{t-1}^i, \underline{y}_{t-1}; \theta) \cdot \chi(\tilde{\underline{\Omega}}_{t-1}^i; \gamma_t) \right] - c_t - \ln\ k(\underline{\Omega}_t; \gamma_t) \right\} \tag{20}$$

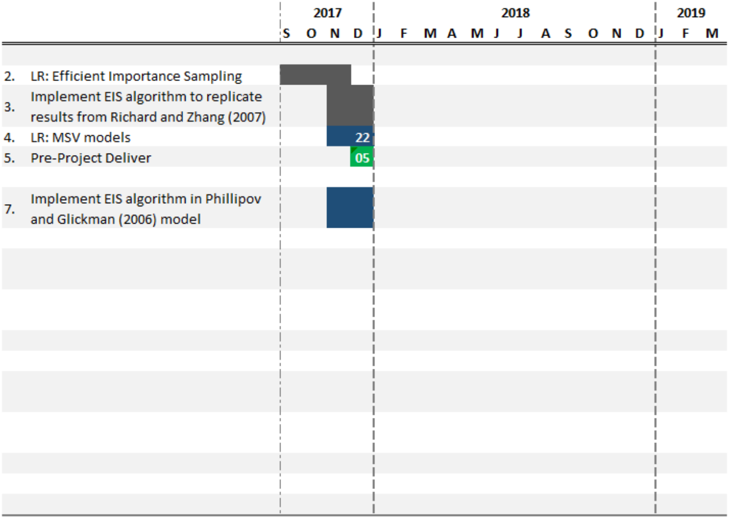
Estimation of a TVP-VAR with MSV via EIS

Workplan - Completed tasks



Estimation of a TVP-VAR with MSV via EIS

Workplan - Econometrics II related tasks



Legend:

Econometrics II article

Macroeconomics II seminar and/or article

Key dates

LR := literature revision

Estimation of a TVP-VAR with MSV via EIS

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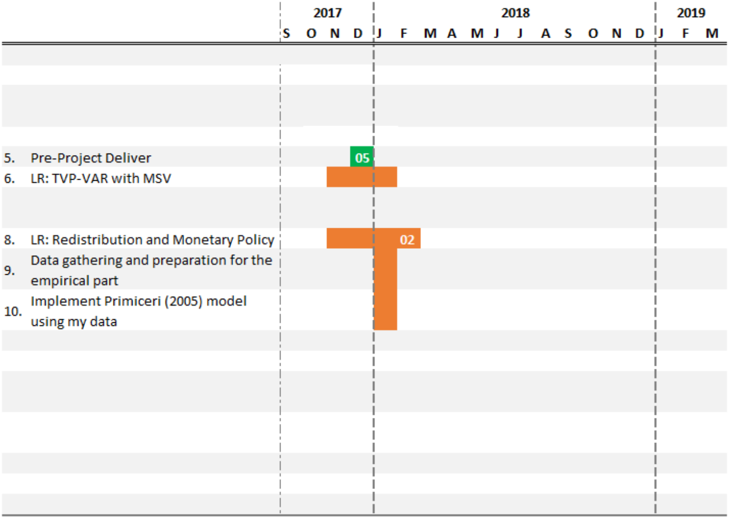

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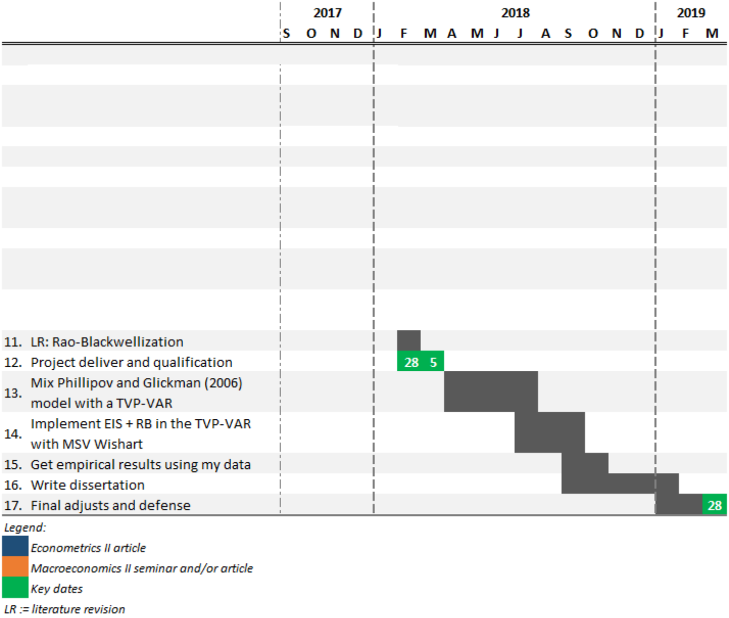
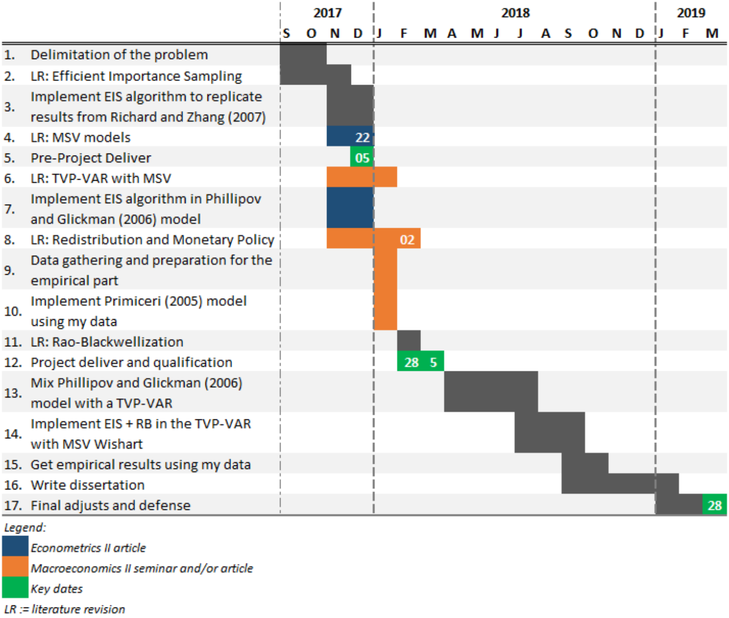
Workplan - What future holds



Estimation of a TVP-VAR with MSV via EIS

Workplan - General Overview



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