

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**
- ▶ 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 volatility structure

Bad luck:

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

Changes in
monetary policy
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Drifting coefficients

Bad policy:

The FED's view negates the natural
rate theory and believes in an
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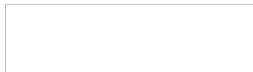
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Phillípov and Glickman (2006a, 2006b)

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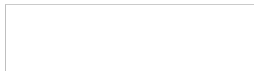
Economic Motivation

TVP-VAR + MSV

Objectives

IS, EIS, Sequential EIS

Sequential EIS + Wishart MSV Model



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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:

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

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

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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:

$$y_t = Z_t \alpha_t + \epsilon_t \quad \epsilon_t \sim \mathcal{N}_k(0_k, R) \quad (3)$$

$$\alpha_t = \alpha_{t-1} + u_t \quad u_t \sim \mathcal{N}_p(0_p, Q) \quad (4)$$

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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 $R_t = B^{-1} H_t B^{-1'}$ with:

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

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

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:

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

where ν_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)

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

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

$$\Omega_t | \Omega_{t-1} \sim \mathcal{W}(\nu, S_{t-1}), \quad \text{with } S_t = \frac{1}{\nu} \mathbf{A}^{1/2} \Omega_t^{\textcolor{red}{d}} \mathbf{A}^{1/2'} \quad (7)$$

where

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

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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?

Primiceri (2005)

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

Philippov and

Estimation
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Estimation of a TVP-VAR with MSV via EIS

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Phillipov and Glickman (2006)

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

Estimation problems

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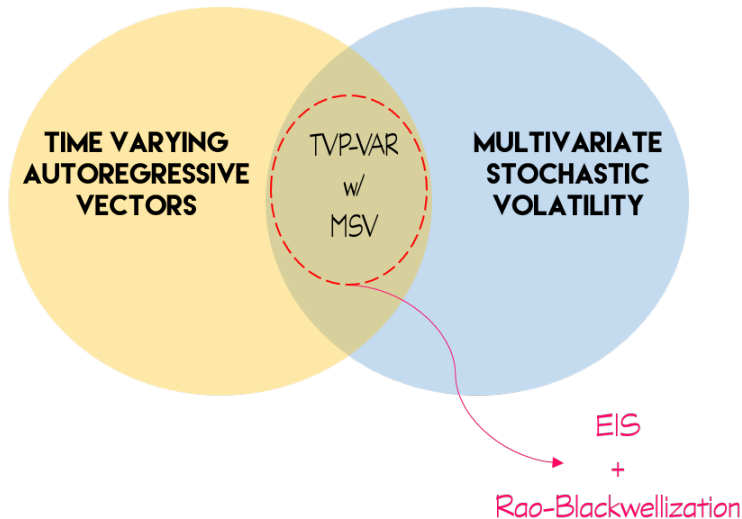
Estimation of a TVP-VAR with MSV via EIS

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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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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3. Develop an empirical application using the model developed in (2), in line with [Mumtaz and Theophilopoulou, 2017].

Estimation of a TVP-VAR with MSV via EIS

Methodology: Monte Carlo Methods and Importance Sampling

- ▶ 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.

Estimation of a TVP-VAR with MSV via EIS

Methodology: Monte Carlo Methods and Importance Sampling

Consider the following integral:

$$I = \int_{\mathcal{X}} g(x)f(x)dx \quad (8)$$

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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 $f(\cdot)$:

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

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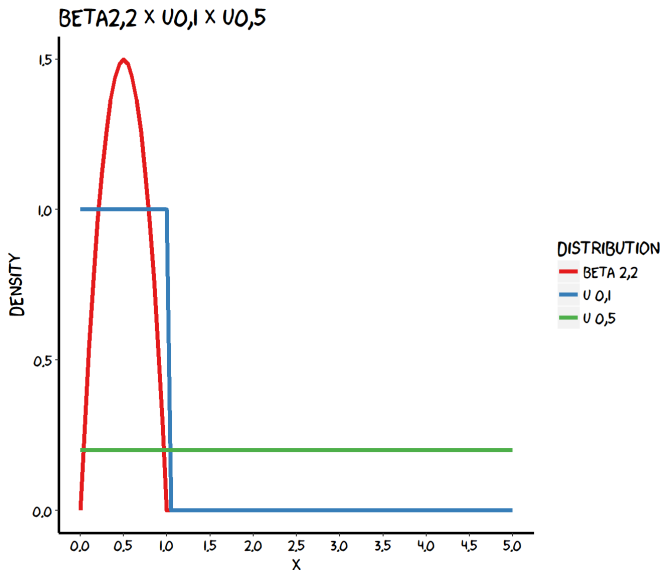
$$I = \mathbb{E}_f[g(x)] \quad (9)$$

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

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

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:

$$I = \int_{\mathcal{X}} g(x) \frac{f(x)}{m(x)} m(x) dx \quad (11)$$

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

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

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

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

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 ;

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Methodology: Efficient Importance Sampling

Two main “problems” arise when dealing with IS:

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Estimation of a TVP-VAR with MSV via EIS

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- ⇒ EIS resolves the last one!

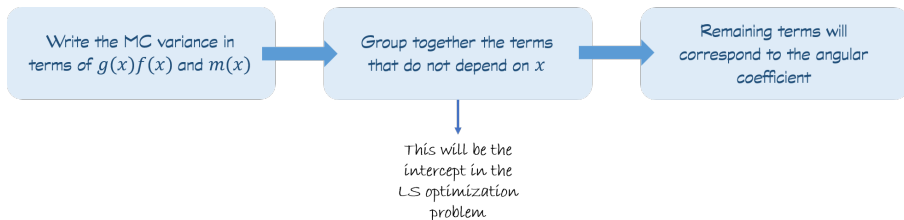
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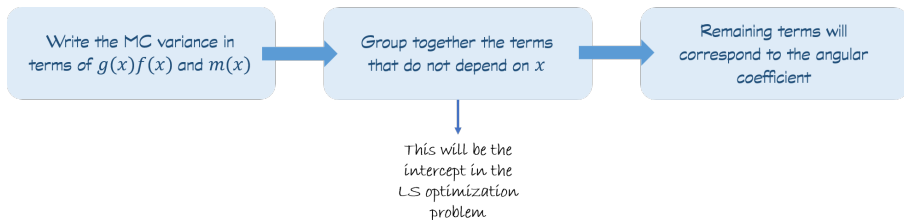
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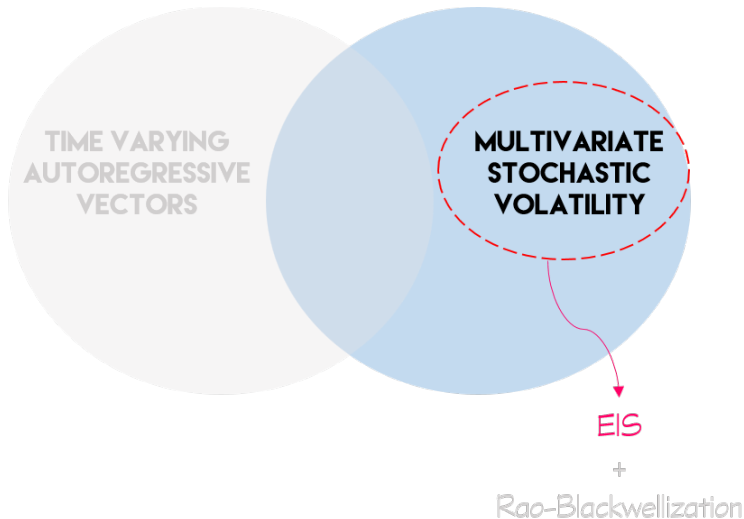
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- ▶ Sequential EIS is used in high-dimensional problems and consists in “breaking” the EIS algorithm in a sequence of low-dimension optimizations.

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:

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

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:

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

where

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

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

Estimation of a TVP-VAR with MSV via EIS

Methodology: Wishart MSV model

Likelihood:

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

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

MC estimate:

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

Minimization problem:

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

Estimation of a TVP-VAR with MSV via EIS

Workplan - Completed tasks

	2017				2018												2019		
	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M
1. Delimitation of the problem																			
2. LR: Efficient Importance Sampling																			
3. Implement EIS algorithm to replicate results from Richard and Zhang (2007)																			
														</					

Legend:

- Econometrics II article
- Macroeconomics II seminar and/or article
- Key dates

LR := literature revision

Estimation of a TVP-VAR with MSV via EIS

Workplan - Econometrics II related tasks

	2017				2018												2019		
	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D	J	F	M
2. LR: Efficient Importance Sampling																			
3. Implement EIS algorithm to replicate results from Richard and Zhang (2007)																			
4. LR: MSV models																			
5. Pre-Project Deliver																			
7. Implement EIS algorithm in Phillipov and Glickman (2006) model																			

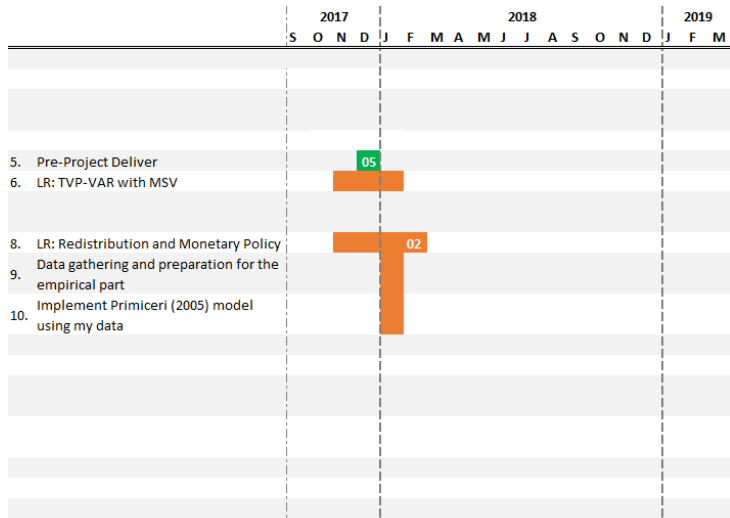
Legend:

- Econometrics II article
- Macroeconomics II seminar and/or article
- Key dates

LR := literature revision

Estimation of a TVP-VAR with MSV via EIS

Workplan - Macroeconomics II related tasks



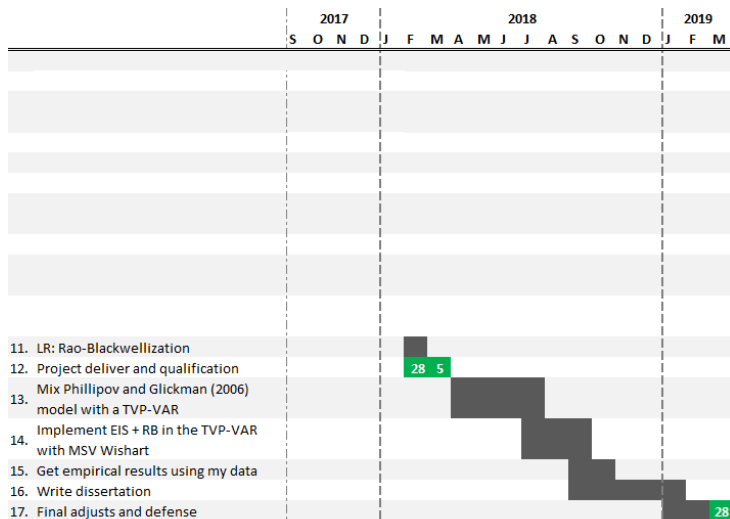
Legend:

- Econometrics II article
- Macroeconomics II seminar and/or article
- Key dates

LR := literature revision

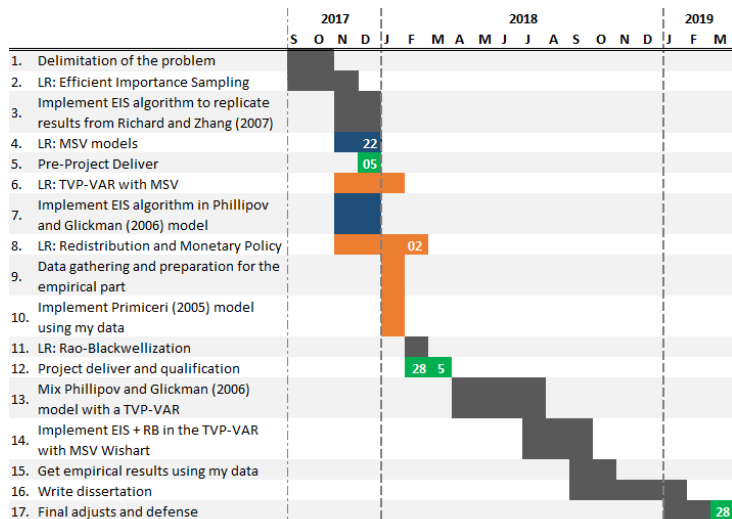
Estimation of a TVP-VAR with MSV via EIS

Workplan - What future holds



Estimation of a TVP-VAR with MSV via EIS

Workplan - General Overview



Legend:

■ Econometrics II article

■ Macroeconomics II seminar and/or article

■ Key dates

LR := literature revision

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