

2.2. Deterministic and Extended Path Simulations

Occasionally Binding Constraints in DSGE Models

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¹The views expressed are those of the authors and should not be interpreted as reflecting the views of the Bank of Canada.

Reminder of the problem

- ▶ We have a DSGE model in the form

$$\mathbb{E}_t f(x_{t+1}, x_t, x_{t-1}, u_t) = 0 \quad (1)$$

which includes a non-differentiable function representing inequality constraints

- ▶ $f(\cdot)$ is a *known* function and the solution implies the unknown policy:

$$x_t = g(x_{t-1}, u_t) \quad (2)$$

- ▶ Projection methods can be used if the model is small, but for larger models, perturbation (e.g. using dynare) will not capture the inequality constraints.
- ▶ One option to simplify the problem is to remove uncertainty, so the model becomes:

$$f(x_{t+1}, x_t, x_{t-1}, u_t) = 0 \quad (3)$$

Perfect Foresight

Perfect-foresight simulation

To solve, we can stack the model over T periods

$$F(X) = \left\{ \begin{array}{c} f(x_0, x_1, x_2, z_1) \\ f(x_1, x_2, x_3, z_2) \\ \vdots \\ f(x_{T-1}, x_T, x_{T+1}, z_T) \end{array} \right\} = 0 \quad (4)$$

Initial and end conditions given ($x_0 = x_{T+1} = \bar{x}$)

- ▶ For an N equation model over T periods, there will be $N \times T$ unknowns and equations
- ▶ Can use a root-finding algorithm to find x to satisfy (4).

Perfect-foresight IRF example

We can write our example model

$$f(b) = \min \{ \mu(b_{t+1}, b_t, b_{t-1}, z_t), (\underline{b} - b_t) \} = 0 \quad (5)$$

where:

$$\mu(b_{t+1}, b_t, b_{t-1}, z_t) = \frac{1}{c(b_t, b_{t-1}, z_t)} - r\beta \left[\frac{1}{c(b_{t+1}, b_t, z_{t+1})} \right] + \delta b_t \quad (6)$$

$$c(b_t, b_{t-1}, z_t) = \frac{1}{1 + \chi} [\exp(z_t) + rb_{t-1} - b_t] \quad (7)$$

- We can substitute out c_t , h_t and μ , so are left with a single equation model (+ shock process)

Perfect-foresight IRF example in Matlab

See code: [/borrowing_constraints/VFI/soe_irf_fsolve.m](#)

- ▶ Solving this example in Matlab is straightforward
- ▶ We can even just use fsolve, setting up a function to return $F(b)$:

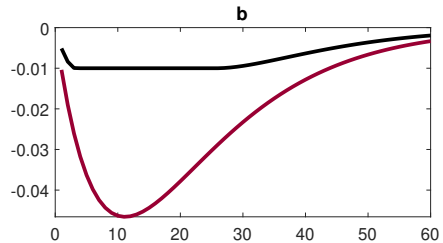
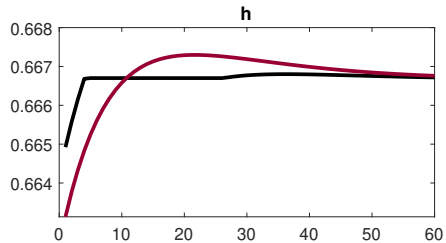
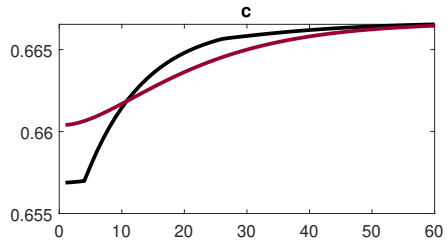
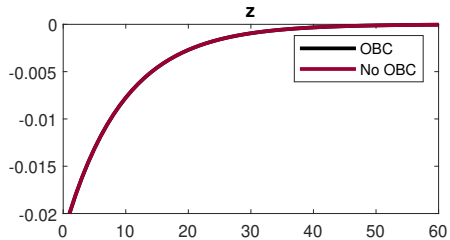
```
1 function F = model_f( b , z , ss , p )
2     lag_b = [ ss.b ; b(1:end-1) ];
3     c = ( exp( z ) + p.r .* lag_b - b ) ./ (1 + p.chi);
4     lead_c = [ c(2:end) ; ss.c ];
5     mu = (1./c) - p.betta * p.r * (1./lead_c) + p.delta .* b;
6     F = min( mu , b-p.b_limit );
7 end
```

and

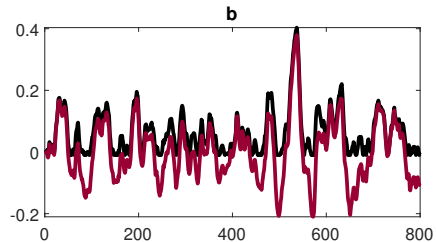
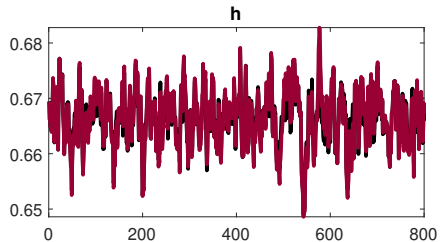
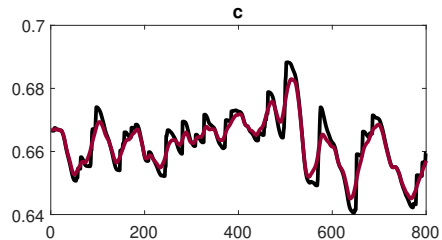
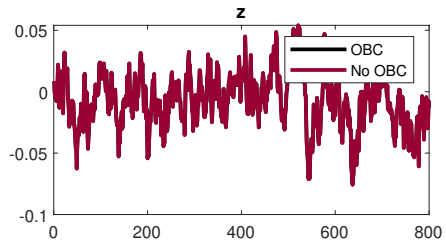
```
1 fun = @(b) model_f( b , z , ss , p );
2 b0 = ss.b * ones( T , 1 );
3 [b , ~ , flag , ~] = fsolve( fun , b0 , options );
```

- ▶ Note: the start and end values, $b_0 = b_{T+1} = \bar{b}$, the steady-state value.
- ▶ The same code can be used to compute simulated time-series (see [soe_ts_fsolve.m](#))

Perfect-foresight IRF



Perfect-foresight Time-series



Perfect-foresight simulation in Dynare

See code: [/borrowing_constraints/VFI/soe_obc.mod](#)

- ▶ To use Dynare's perfect foresight solver, you must specify the shocks:

```
1 || shocks;  
2 ||     var epsz; periods 1; values -2;  
3 || end;
```

- ▶ and replace the `stoch_simul` command with:

```
1 || simul( periods=400 );
```

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- ▶ Variety of algorithms to choose from - default is a Newton-type method.
 - ▶ This is an iterative procedure, which for a single variable would be written:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} \quad (8)$$

OBC considerations - LMMCP 1/2

- ▶ The presence of min/max operator can introduce a singularity into the Jacobian
 - ▶ We may fail to converge to a solution
- ▶ Dynare can improve on the default Newton method by treating it as a Levenberg-Marquardt mixed complementarity problem (LMMCP)
- ▶ This specifically deals with inequality constraints

OBC considerations - LMMCP 1/2

- ▶ The constraint must be given, replacing the min/max operator
 - ▶ i.e., the complimentary slackness condition

The equation in

```
1 || model
2 ||     ...
3 ||     b = max( exp(z) + r*b - 1 / (betta*r*(lead_muc) + p.delta ) , b_limit);
4 ||     ...
5 || end
```

is replaced with:

```
1 || [mcp = 'b > -0.01'] b = exp(z) + r*b - 1 / (betta*r*(lead_muc) + p.delta );
```

- ▶ The LMMCP option is switched on in the `simul` command:

```
1 || simul( periods=400 , lmmcp );
```

Perfect-foresight Dynare – comments

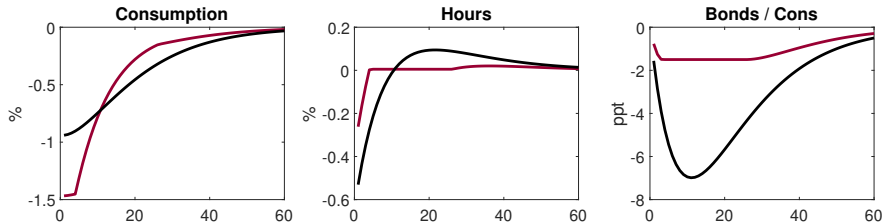
Performance:

- ▶ Robustness of Newton-type method improved recently via homotopy
 - ▶ Progressively increases shock scale, helping models which are difficult to solve
- ▶ The LMMCP can help with hard-to-solve problems
- ▶ Still the methods are slow and unreliable
- ▶ It is difficult to tell if non-convergence is to because there is no solution

Accuracy:

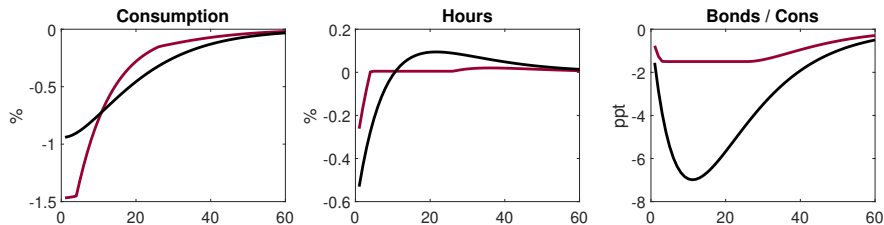
- ▶ Captures model non-linearities, including OBCs
- ▶ Perfect-foresight IRF has a natural interpretation
- ▶ Can also simulate response to *news* of a future shock, or transitions between long-run equilibria (absent uncertainty)
- ▶ Simulated time-series do not have a natural interpretation – perfect anticipation

Perfect foresight: IRF to large technology shock

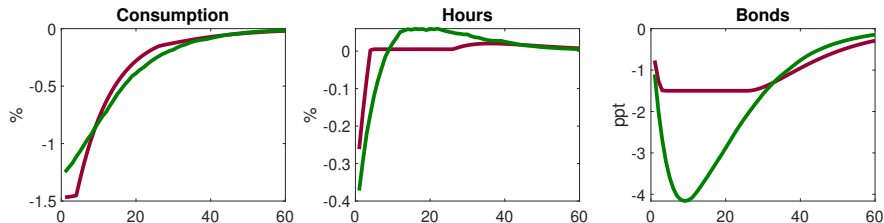


► No constraint, with OBC

Perfect foresight: IRF to large technology shock



► No constraint, **with OBC**



► Projection (deviation from ergodic mean), **perfect foresight (Newton method)** (dev. from SS)

Extended Path

Extended path simulations

The previous approach assumes the perfect foresight of shocks

Alternatively we could assume firms and households are always surprised by shocks

- ▶ Every period they observe current and past shocks, and expect future shocks to equal zero

The underlying numerical problem is the same:

- ▶ Every period the perfect foresight simulation is solved to compute current decisions
- ▶ This is the [Fair & Taylor \(1983\)](#) extended-path method and is invoked in dynare using:

```
1 || extended_path(order="0", periods="10000");  
    instead of simul or stoch_simul.
```

See code: [/extended-path/soe_obc.m](#)

Extended path simulations in Matlab

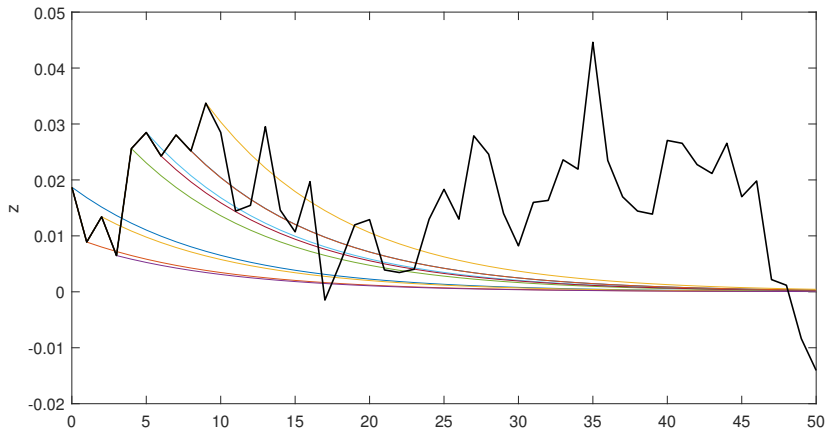
The extended path algorithm builds on the perfect-foresight solver.

- ▶ We can again easily demonstrate this in Matlab using `fsolve`
- ▶ see code: [/extended-path/soe_ts_ep.m](#)

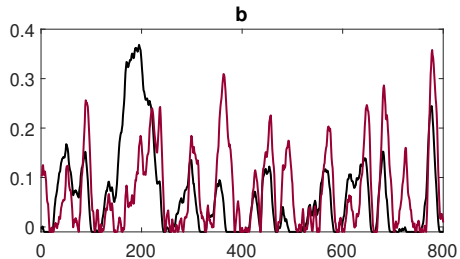
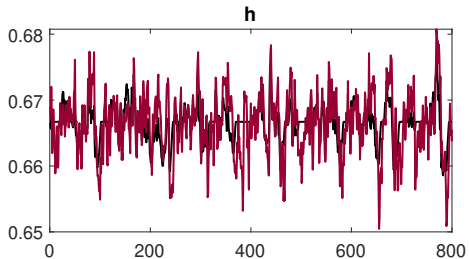
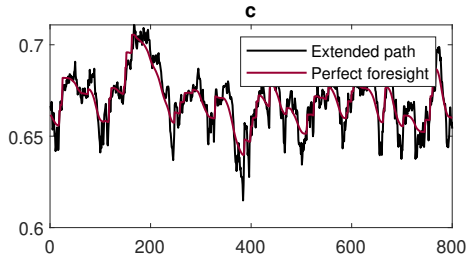
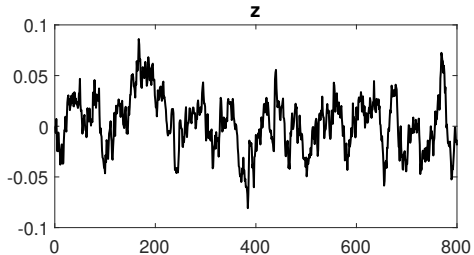
Extended path simulations in Matlab

The extended path algorithm builds on the perfect-foresight solver.

- ▶ We can again easily demonstrate this in Matlab using `fsolve`
- ▶ see code: [/extended-path/soe_ts_ep.m](#)
- ▶ Actual series for z (black), with expected path at different points in time.



Extended-path vs perfect foresight simulations



Stochastic Extended-Path Algorithm

Dynare has an adapted extended-path algorithm to incorporate the role of risk

The *stochastic* extended-path algorithm computes expectations every period up to a finite horizon

The **first** step is to draw a random path for all exogenous variables

Second, Dynare computes the corresponding path for the endogenous variables using the algorithm:

1. An integer k is chosen which is the number of periods for which expectations must be computed.
2. Beginning with expectations equal to the steady-state values $\mathbb{E}_s x_{s+r} = x$ for $r = 0, \dots, k$, obtain a new set of expectations by solving the non-linear model dynamically. Every period the expectations are evaluated using a Gaussian quadrature.
3. Setting the new expectations as the starting values, this is repeated until convergence.
4. Repeat the above but increasing r by 1 and repeat this until convergence.

(Stochastic) Extended-Path in dynare

Shocks are specified as when using `stoch_simul`, but instead use:

```
|| extended_path(order="16", periods="10000");
```

(Stochastic) Extended-Path in dynare

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```
|| extended_path(order="16", periods="10000");
```

In practice, the extended-path method in dynare doesn't solve the full rational expectations model. The modeller specifies the maximum value of k for which to solve using the `order` option

- ▶ In this case, expectations are computed as if shocks could be non-zero for 16 more periods. After this horizon, the agents would believe that there would be no more future shocks.
- ▶ For accuracy, the order should be set to be the same magnitude as the decay of the model.
- ▶ dynare uses Gaussian quadrature to evaluate the expectations which scales exponentially in the number of shocks and the order (although not the number of states).
- ▶ In practice, solving with sufficient accuracy is infeasible even for very small models.
- ▶ The accuracy improvement seems small compared to the significant computational cost.

Simulated Moments

Projection results:

	Mean	Standard deviation	Skewness	
	Relative to no constraint	Relative to no constraint	Baseline	No constraint
Consumption	+0.03%	+15%	-0.22	0.09
Hours	-0.01%	-43%	-0.09	-0.04
Bonds / \bar{c}	0.3% \rightarrow 5%	-59%	1.18	0.007

All methods:

		Mean	Standard deviation	Skewness
		Relative to projection	Relative to projection	(projection)
VFI	Consumption	≈ 0	+0.02%	-0.23 (-0.22)
	Hours	≈ 0	+0.6%	-0.09 (-0.09)
	Bonds / \bar{c}	5.0% \rightarrow 4.9%	<1%	1.18 (1.18)
Extended-path	Consumption	-0.03%	+0.5%	-0.29 (-0.22)
	Hours	+0.003%	+1%	-0.1 (-0.09)
	Bonds / \bar{c}	5.0% \rightarrow 4.0%	-1.4%	1.3 (1.18)

References I

Fair, R. C. & Taylor, J. B. (1983), 'Solution and Maximum Likelihood Estimation of Dynamic Nonlinear Rational Expectations Models', *Econometrica* **51**(4), 1169–1185.