DSGE Modeling with Cognitive Discounting

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1. Research Question

Does incorporating **cognitive discounting** affect the empirical conclusions and properties of DSGE models?

2. Motivation

- The prominent macroeconomic tool that uses people's beliefs and expectations for policy analysis and forecasting is the dynamic stochastic general equilibrium (DSGE) model
- Empirical work with DSGE models have mostly used the rational expectations hypothesis which assumes complete attention and full information/understanding about the future; this has come under scrutiny e.g. Stiglitz (2018)
- An alternative approach has been bounded rationality, specifically through **cognitive discounting, or "myopia", where consumers and firms pay less attention to variables that are further into the future**; recent research has suggested the existence of myopia and explored its impact on the US economy

3. Expectations in DSGEs

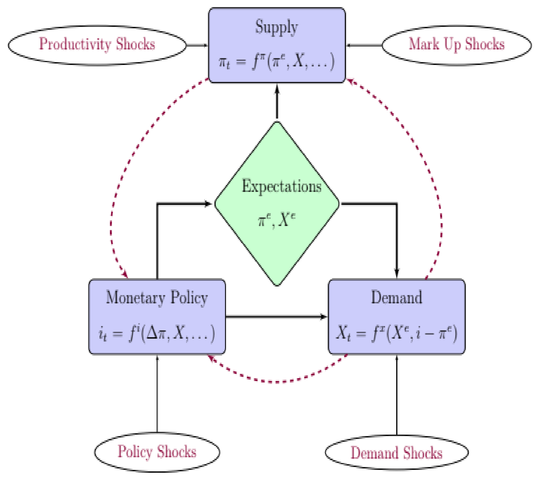

Figure 1: People's expectations play a crucial role in this basic DSGE ecosystem. Monetary policy through the interest rate (i_t) influences expectations about inflation and output in the future (π^e, X^e), which in turn are used in determining both inflation and output today. Output and inflation today are then used in determining what the monetary policy nominal interest rate will be.

4. Approach

- I incorporate a cognitive discounting parameter à la Gabaix (2016) for myopia $\bar{\mathbf{m}}$ into the behavioral forward-looking equations for consumption and inflation in the linearized DSGE model of Smets and Wouters (2007) which has formed the basis for many central bank DSGE models:

$$c_t = c_1 c_{t-1} + \bar{\mathbf{m}}(1-c_1)\mathrm{E}_t(c_{t+1}) + c_2(l_t - \mathrm{E}_t(l_{t+1})) - c_3(r_t - \mathrm{E}_t(\pi_{t+1})) + \varepsilon_t^b \tag{1}$$

$$\pi_t = \pi_1\pi_{t-1} + \pi_2 \mathbf{M^f}\mathrm{E}_t(\pi_{t+1}) - \pi_3\mu_t^p + \varepsilon_t^p, \qquad M^f = \bar{m}\left[\xi_p + \frac{(1-\beta\xi_p)(1-\xi_p)}{1-\beta\xi_p\bar{m}}\right] \tag{2}$$

  where $c_1, c_2, c_3, \pi_1, \pi_2, \pi_3$ are coefficients given in Smets and Wouters (2007) composed of parameters; $\bar{m} = 1$ gives the standard equations and means no myopia
- Using the Bayesian likelihood approach in Smets and Wouters (2007), I model myopia using a prior distribution used by Ilabaca, Meggiorini, and Milani (2020), who find substantial degrees of myopia between 1954 and 2007
- I investigate the importance of myopia on the parameters in the model through general equilibrium estimation and compare the results to the posterior estimates from Smets and Wouters (2007) in Section 5

5. Bayesian Estimation Comparison

This table gives the parameter means and 95% high density interval (HDI) of the posterior distributions obtained by the Metropolis-Hastings algorithm. The 95% HDI is not a traditional confidence interval; it shows the central portion of the posterior distribution that contains 95% of the values. A sample of 250,000 draws were created neglecting the first 50,000. Direction change of the mean is given by the Δ column. All other parameters/shocks did not change from the benchmark case.

Prior and Posterior Distribution of Selected Parameters and Shocks

	Prior			*Smets and Wouters (2007)*			Posterior with Myopia			Δ
	Distr.	Mean	St. Dev.	*Mean*	*5%*	*95%*	Mean	5%	95%	
φ	Normal	4.00	1.50	*5.74*	*3.97*	*7.42*	5.98	4.22	7.65	↑
σ_l	Normal	2.00	0.75	*1.83*	*0.91*	*2.78*	1.59	0.66	2.52	↓
r_π	Normal	1.50	0.25	*2.04*	*1.74*	*2.33*	1.97	1.68	2.26	↓
$\bar{\pi}$	Gamma	0.62	0.10	*0.78*	*0.61*	*0.96*	0.74	0.57	0.91	↓
$\bar{l}$	Normal	0.00	2.00	*0.53*	*-1.30*	*2.32*	0.21	-1.27	1.64	↓
ρ_r	Beta	0.50	0.20	*0.15*	*0.04*	*0.24*	0.14	0.04	0.23	↓
ρ_p	Beta	0.50	0.20	*0.89*	*0.80*	*0.96*	0.87	0.78	0.96	↓
σ_a	Invgamma	0.10	2.00	*0.45*	*0.41*	*0.50*	0.46	0.42	0.51	↑
σ_i	Invgamma	0.10	2.00	*0.45*	*0.37*	*0.53*	0.44	0.36	0.52	↓
σ_p	Invgamma	0.10	2.00	*0.14*	*0.11*	*0.16*	0.15	0.12	0.17	↑
$\bar{m}$	Beta	0.80	0.15	–	–	–	0.98	0.96	0.99	–

6. Findings/Next Steps

Incorporating myopia generally **decreases** the posterior parameter means and tightens their HDI. **However**, marginal likelihood of the DSGE with myopia is -922.65 versus -905.33 without, suggesting that this integration of myopia is not preferred in matching data. Key insights:

- **Labor** Steady state labor ($\bar{l}$) and the elasticity of labor supply with respect to wage (σ_l) fell, implying a smaller marginal rate of substitution between working and consuming
- **Shocks** Monetary policy and price mark up shocks have smaller AR coefficients (ρ_r, ρ_p) implying less persistence
- **Myopia** Appears to exist in a tight interval just below unity

Useful extensions of this project could be merging myopia differently and choosing another prior distribution, and generating forecasts variance decomposition for variables like output.

8. References

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