Incentive-driven Inattention

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Overview

- A Brazilian dataset on daily forecast by professional forecasters
 - Every day, about 10% of forecasts are updates
 - Mid-month a contest is organized, 40% update then
 - Updating reduces the MSFE and disagreement
- This paper explores determinants of decision to update and amount of effort
 - Model of rational inattention
 - Matches the data
 - Counterfactuals

Overview of the Discussion

The model

Assumptions

- intertemporal decisions
- private/public information and timing
- identification of decision to update vs amount of attention
- weekends
- Method of Simulated Moments
 - weak identification
 - persistence

1. The model

• Principles: daily decisions, t = 0, ..., T about forecasts of monthly inflation $y_m = \sum_{t=1}^{T} x_t$ where

$$x_t = b + \phi x_{t-1} + \varepsilon_t, \quad \varepsilon_t \stackrel{iid}{\sim} \mathsf{N}\left(0, \sigma_{\varepsilon}^2\right)$$

• Timing: at t = 0, a monthly forecast is made then at t > 0,

- Agent *i* decides to update forecast if marginal benefit of allocated time $\tilde{w}_{it} > w_{it}^0$
- (a) if update, then observe $\mathcal{I}_{t-1} = \{x_{t-1}, ...\}$ and choose k_{it} is attention spent to observing ε_t , rationality is $k_{it} \to \infty$ Forecast: $x_{t|t} = b + \phi x_{t-1} + \mathbb{E}[\varepsilon_t | k_{it}]$

$$\mathsf{MSFE}_{it}(k_{it}) = \mathsf{E}\left[(y_m - \mathsf{E}\left[y_m | \mathcal{I}_{t-1}, k_{it}\right])^2\right] = \sigma_{\varepsilon}^2 A_{T-t} + B_{T-t} \mathsf{E}\left[(\varepsilon_t - \mathsf{E}\left[\varepsilon_t | k_{it}\right]\right] + \mathsf{E}$$

Quantum Rational inattention (Sims, 2003): E [(ε_t - E [ε_t|k_{it}])²] = 2^{-2k_{it}}σ_ε².
Objective at time t :

$$\min_{\left(k_{i\tau}\right)}\sum_{\tau=t}^{T}\left(\frac{w_{i\tau}}{2\ln 2}\mathsf{MSFE}_{\tau}\left(k_{i\tau}\right)+c_{\tau}k_{i\tau}\right)\mathbf{1}_{\left(\tilde{w}_{i\tau}>w_{i\tau}^{0}\right)},$$

 w_{it} benefit of accuracy, c_t cost of attention.

• At each t, a static problem,

$$\begin{split} \min_{k_{it}} \left(\frac{w_{it}}{2 \ln 2} \mathsf{MSFE}_t \left(k_{it} \right) + c_t k_{it} \right) \mathbf{1}_{\left(\tilde{w}_{it} > w_{it}^0 \right)},\\ \mathsf{MSFE}_t \left(k_{it} \right) &= \sigma_{\varepsilon}^2 A_{T-t} + \sigma_{\varepsilon}^2 B_{T-t} \times 2^{-2k_{it}}, \quad k_{it} \ge 0, \end{split}$$

simplified as $k_{it} > 0$ if $\tilde{w}_{it} > w_{it}^0$ and $\tilde{w}_{it} = w_{it}$ so

$$\mathsf{MSFE}_{t}\left(k_{it}\right) = \begin{cases} \sigma_{\varepsilon}^{2} A_{T-t} + c_{t} w_{it}^{-1}, & \text{if } w_{it} > c_{t} / \sigma_{\varepsilon}, \\ \mathsf{MSFE}_{t-1}\left(k_{it-1}\right), & \text{otherwise.} \end{cases}$$

- This paper's questions on exogenous variables
 - $w_{it} \sim D(\mu_w, \sigma_w^2)$ reflects the gains from accuracy: μ_w larger on Competition Day?
 - 2 c_t is the cost of information: smaller on IPCA15 day?

2.A. Assumption: no dynamic substitution of attention

- The problem is a static allocation of attention.
- $w_{it} > 0$ implies there is a cost attributed to all forecast errors. In their objective function, agents only consider cost of forecast errors if update

$$\min_{(k_{i\tau})} \sum_{\tau=t}^{T} \left(\frac{w_{i\tau}}{2 \ln 2} \mathsf{MSFE}_{\tau} \left(k_{i\tau} \right) + c_{\tau} k_{i\tau} \right) \mathbb{1}_{\left(\tilde{w}_{i\tau} > w_{i\tau}^{0} \right)},$$

• but if $k_{i\tau} = 0$ then $MSFE_{\tau}(k_{i\tau}) = MSFE_{\tau-1}(k_{i\tau-1})$ so why not consider the entire stream of forecasts?

$$\min_{\left(k_{i\tau}\right)}\sum_{\tau=t}^{T}\frac{w_{i\tau}}{2\ln 2}\mathsf{MSFE}_{\tau}\left(k_{i\tau}\right)+c_{\tau}k_{i\tau}\mathbf{1}_{\left(\tilde{w}_{i\tau}>w_{i\tau}^{0}\right)}$$

• Now decisions depend on future profiles of w_{it} and c_t so agents anticipate, e.g., Competition days and IPCA15 releases. They know their forecast errors linger so they may exert more effort before a planned increase in c_{t+1} or w_{it+1} 2.B. Private vs public information and timing of decisions

Here

- Agents first decide whether to update then they observe public information
- Agents decide on the level of attention to ε_t, a public/common signal that is costly to acquire (*private*?)
- Timing swapped in Bec, Bouccekkine & Bardet (2017, BoFrance) who use Alvarez, Lippi & Paciello (2011, QJE)
 - Agents decide when to observe public information and hence the optimal forecast
 - Then whether to communicate/update their official forecast (is it worth adjusting given the time left until the realization?)

Empirically: adjustment costs < cost of acquiring information

2.C. Assumption 5: If agents update, they devote positive attention

- Hard to distinguish decision to update from that of paying attention
- Agents may simply decide to update using only the public signal:

$$MSFE_{t}(0) - MSFE_{t-1}(k_{t-1}) = -\left[\frac{1-\phi^{T-t+2}}{1-\phi}\right]^{2} \mathsf{E}\left[\left(\varepsilon_{t-1} - \mathsf{E}\left[\varepsilon_{t-1}|k_{it-1}\right]\right)^{2}\right]^{2} \mathsf{E}\left[\left(\varepsilon_{t-1} - \mathsf{E}\left[\varepsilon_{t-1}|k_{it-1}\right]\right]^{2} \mathsf{E}\left[\left(\varepsilon_{t-1} - \mathsf{E}\left[\varepsilon_{t-1}|k_{it-1}\right]\right)^{2}\right]^{2} \mathsf{E}\left[\left(\varepsilon_{t-1} - \mathsf{E}\left[\varepsilon_{t-1}|k_{it-1}\right]\right]^{2} \mathsf{E}\left[\left(\varepsilon_{t-1} - \mathsf{E}\left[\varepsilon_{t-1}|k_{it-1}\right]\right)^{2}\right]^{2} \mathsf{E}\left[\left(\varepsilon_{t-1} - \mathsf{E}\left[\varepsilon_{t-1}|k_{it-1}\right]\right]^{2} \mathsf{E}\left[\left(\varepsilon_{t-1} - \mathsf{E}\left[\varepsilon_{t$$

• It would be useful to find a way to fully distinguish between the decision to update and then the amount of attention, not just a decision about $k_{it} \in [0, \infty)$.

2.D Daily inflation forecasts

Past daily inflation {x_{t-1}, ..., x₁} is public information at time t and agents forecast

$$y_m = \sum_{\substack{\tau=1\\observed}}^{t-1} x_{\tau} + \sum_{\tau=t}^{T} x_{\tau}$$

- Weekends: 3-day forecasting exercise on Fridays so we expect more updates/effort, $3/7\approx 0.4$
 - ► Here: T is the number of working days \rightarrow then the distribution of x_t differs on Mondays
 - ► Alternatively, use *T* : calendar days and explicitely consider the three-day forecasting exercise on Fridays.
- Focusing on daily inflation is a nice way to convey the idea
 - > Yet, under the model, the release of IPCA15 is **private** (not public) information but it occurs on day $t \approx 20-22$ so it should already be observed.
- Is it reasonable to assume individual agents (not representative) know the DGP for daily inflation over the coming year (estimated ex post by the econometrician)

3.A. Method of Simulated Moments: Weak identification

• Probability to update $\lambda_t = \Pr\left(w_{it} > \frac{c}{\sigma_c^2}\right)$ with $w_i \sim TN(.49, .06^2)$ and

 $\frac{c}{\sigma_e^2} = \frac{1.4 \times 10^{-5}}{.005^2} = .56$

• Distribution of attention k_{it} conditional on updating or not, (T = 25)



Method of Simulated Moments: Weak identification

- Probability to update $\lambda_t = \Pr\left(w_{it} > \frac{c}{\sigma_z^2}\right)$ with $w_i \sim TN(.49, .06^2)$ and
 - $\frac{c}{\sigma_e^2} = \frac{1.4 \times 10^{-5}}{.005^2} = .56$
- New parameters, (T = 25)



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3.B Method of Simulated Moments: persistence

- Inflation is known to be persistent (Altissimo, Monjon & Zaffaroni, 2009)
- Here ARMA(1, 1) monthly inflation estimated over 2000-2009 implies for daily (approx.)

$$x_t = 7 \times 10^{-4} + .98x_{t-1} + \varepsilon_t$$
, $\varepsilon_t \sim N\left(0, .0025^2\right)$

almost a random walk.

• ARFIMA for monthly

$$\Delta^{.33}_{(.08)} y_m = .52_{(.18)} \left(1 + .37_{(.08)} L \right) v_t$$

better fit (AIC) than ARMA(1, 1).

- If agents forecast with AR(1) processes with slope φ_i, the aggregate forecast may be persistent (Granger, 1980)
- Consequences: long term forecast errors dominate, MSFEs correlate, forecasts may be biased... MSM may be very susceptible to initialization of the algorithm.

A cool dataset An interesting model A nice paper to read!

Thanks!