Short- and Long-run dynamics in Electricity Markets using MIP tools

DSE Summer School

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Outline

I. Models of electricity markets

- Reducing complexity via dimension-reduction techniques
- Handling dynamics in the electricity sector

II. Two teasers

- Gonzales, Ito, and Reguant (2023)
- Gowrisankaran, Langer, and Reguant (2024)

III. Computational tools for short-run dynamics

- Clearing in electricity markets
- Modeling with JuMP (Julia)
- Models with complemetarities

I. Models of electricity markets

Electricity markets are becoming a key aspect of decarbonizing our economies

- Need to reduce greenhouse gases (GHGs) to near zero.
- The electricity sector ($\approx$ 35-40% of CO_2 emissions) among the most actives due to its larger potential to offer solutions.
- Several countries and states have an ambition of net-zero electricity by 2035.

How? Four (main) dimensions of change

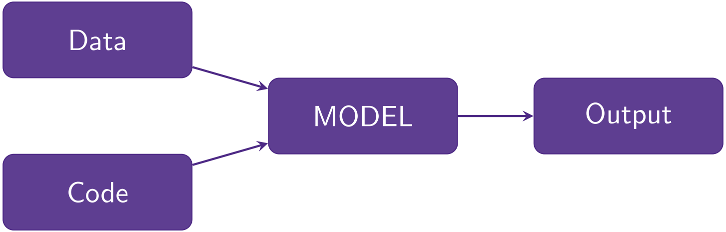
- Renewables + batteries
- Energy efficiency
- Demand response
- Electrification of other sectors, other forms of clean energy

A straightforward problem statement but a highly complex system

- At its heart, all electricity market models have firms/technologies and information about demand (as a curve or fixed) to find the best allocation that ensures demand = supply (called economic dispatch).
- If the model takes into account discrete decisions about which power plants to turn on/off, it is called a unit committment problem (more difficult to solve) to which we might add low-frequency investment decisions.

- Depending on the question at hand, the electricity markets in economic analysis are modeled abstracting away from many features.
  - E.g., big long-run policy questions like climate policy might be answered with a simplified version of the market.
- Depending on the question, some more detailed features need to be brought back.
  - E.g., transmission congestion regarding renewable expansion.

Building models of electricity markets



- Model used to simulate impact of alternative configurations, profitability of investments, impacts of climate policies, etc.
- Does output for baseline match data? If not, do we need to expand code?
  - Not always, keep an eye on things that are important to our question and that we might not be matching well. A model is a simplification of a complex reality.

Complexity of the model depends on the question at hand

Common elements and options

- Supply side
  - Competitive (cost curves) or strategic (firms max profit)
  - At tech, firm, or plant level
  - With or without geography (transmission, usually with direct current approximation)
  - With or without startup costs (non-convexities)
- Demand side
  - Inelastic or responsive
  - Granular or aggregated

Horizon and temporal linkages

- Level of aggregation
  - Hourly, daily, etc.
- Links between hours
  - Every hour independent from each other vs. temporal linkages (important for storage or startup costs)
- Horizon of choice
  - Day-to-day operations
  - Seasonal water storage
  - Capacity expansion model (investment)

Dimension-reduction techniques can be a first step

- Electricity markets are highly complex.
- Electrical engineers often work with representative cases to make their contributions comparable, but they have limited empirical relevance.
- When analyzing one market in detail with historical data, analysis can become slow.
- Slow computations can lead to limited sample sizes (e.g., three months) or limited counterfactual/econometric analysis (e.g., no standard errors, limited policy analysis).
- Machine learning techniques can be used to reduce the size of the data.

Simplifying the data

- Key idea is to identify "representative hours" with some "weights" for how important each hour or location is.
- These representative hours can then be used in the model (together with the weights) to ensure that the model is representative (but runs much faster).

- *Note:* The hourly clustering is easiest, but it treats each hour as independent. Depending on the problem, clustering days or weeks might be better.
  - E.g., for a short-term battery problem, need to look at battery behavior for at least three days; for hydro, very difficult to cluster due to seasonal rains and long-term storage.

Clustering of different dimensions

- Dimension reduction techniques can be used in many ways to reduce the computational demands of electricity market models.
- Today: application simplifies the time dimension.

- Other examples:
  - Types of consumers with highly dimensional smart-meter data (e.g., see Cahana et al, 2022).
  - Geographical granularity to simplify nodal market data (e.g., see Mercadal, 2021; Gonzales, Ito and Reguant, 2023).
  - Types of production units to simplify technologies in the model.
  - State space for long-run dynamics (e.g., see Gowrisankaran, Langer, and Reguant, 2024).

Dynamics in electricity

Several dimensions involve dynamics:

- Startup of power plants (Reguant 2014; Cullen, 2015).
- Allocation of hydro resources (Crampes and Moreaux, 2001; Bushnell, 2003).
- Batteries (Karaduman, 2021; Butters, Dorsey and Gowrisankaran, 2022).
- Divestitures (Linn and MacCormack, 2019; Gowrisankaran, Langer, and Reguant, 2024).
- Renewable entry (Gonzales, Ito, and Reguant, 2023).

Implementation in each of the papers can be widely different from a technical perspective!

Careful choices in dynamics are also necessary

In any sector, important to decide how dynamics are modeled:

- Level of aggregation: hourly, monthly, annual?
- One-shot vs. multiple periods?
- Stationary infinite horizon vs. finite horizon?
- Relevant dynamic variables vs. those that can be simplified?
- Strategic vs. competitive vs. social planner under dynamics? When are the last two equivalent?

Breaking up short- and long-run

Several dimensions involve dynamics:

- Oftentimes modeling can be broken down into two nests:
  - Short-run hourly nest (with or without dynamics)
  - Long-run investment nest (with or without dynamics)

  Note: Recursive vs. finite horizon formulation a question in both depending on complexity of state space, relevant horizon, and degree of "recursiveness".

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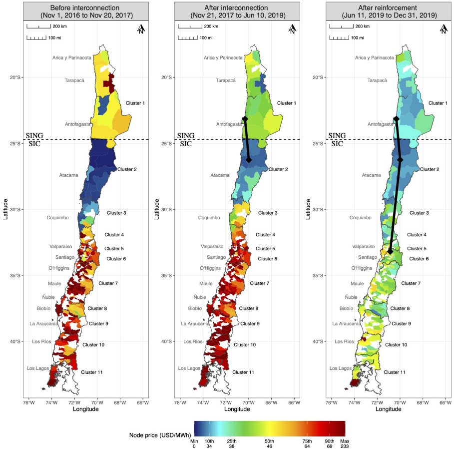
Overview of papers' methods

	Short-run Hourly Models	Long-run Models
GIR (2023)	■ Weekly/monthly models ■ Water and ramping dynamics ■ Stylized transmission model	■ Static long-run zero profit condition ■ (Fancier model for revisions but ultimately simple!)
GLR (2024)	■ Annual "representative" model ■ Ramping dynamics ■ Utilization/total cost annual decision	■ Three-year decisions on investments ■ Some uncertainty on commodity prices ■ Finite horizon with final recursive state

↓
No uncertainty

Gonzales, Ito, and Reguant (2023)

- Gonzales, Ito, and Reguant (2022) quantify the value of transmission infrastructure in Chile.
- **Question**: What is the cost benefit of the expansion project?
- **Tools**: event study + structural model of the Chilean electricity market.
- **Findings**:
  - We highlight the dynamic benefits of grid expansion, enabling increased renewable expansion.
  - The cost of transmission can be quickly recovered, even when ignoring the added climate change benefits.



Static impacts: Event study effects of the line

$$c_t = \alpha_1 I_t + \alpha_2 R_t + \alpha_3 c_t^* + \alpha_4 X_t + \theta_m + u_t$$

- Our method uses insights from Cicala (2022)
  - c_t is the observed cost
  - c_t^* is the nationwide merit-order cost (least-possible dispatch cost under full trade in Chile)
  - $I_t = 1$ after the interconnection; $R_t = 1$ after the reinforcement
  - X_t is a set of control variables; θ_t is month fixed effects
  - α_1 and α_2 are the impacts of interconnection and reinforcement

Static impacts: Event study effects of the line

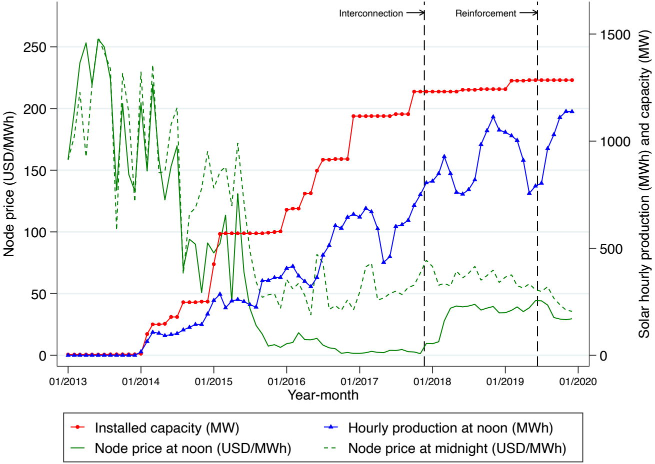
	Hour 12		All hours	
1(After the interconnection)	-2.42	(0.26)	-2.07	(0.17)
1(After the reinforcement)	-0.96	(0.58)	-0.61	(0.37)
Nationwide merit-order cost	1.12	(0.03)	1.03	(0.01)
Coal price [USD/ton]	-0.03	(0.01)	-0.01	(0.01)
Natural gas price [USD/m^3]	-10.36	(4.33)	-0.65	(3.09)
Hydro availability	0.43	(0.14)	0.00	(0.00)
Scheduled demand (GWh)	-0.51	(0.13)	-0.01	(0.00)
Sum of effects	-3.38		-2.68	
Mean of dependent variable	35.44		38.63	
Month FE	Yes		Yes	
Sample size	1033		1033	
R^2	0.94		0.97	

Does this static event study analysis get the full impact?

- Our theory based on the timing of investment effects:
  - Yes if solar investment occurs simultaneously with integration
  - No if solar investment occurs in anticipation of integration

Solar investment occurred in anticipation of integration

- Investment occurred in the anticipation of the profitable environment
- [→] Static analysis does not capture the full impact of market integration
- [→] We address this challenge witth a structural model



Northwestern

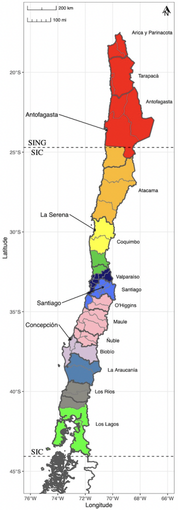
Buidling a model to get at the full effect

- Impacts of the grid can be static and dynamic:
  - Production benefits: more solar can be sent to the demand centers, prices in solar regions go up.
  - Investment benefits: more solar power is built.

- We highlight that an event study is likely to capture only the first kind of effects (e.g., around time of expansion).
- We build a model of the Chilean electricity market to quantify the benefits of market integration including its investment effects.

A structural model to study a dynamic effect on investment

- We divide the Chilean market to five regional markets with interconnections between regions (now expanding to 11)
- Model solves constrained optimization to find optimal dispatch that minimizes generation cost
- Constraints:
  1. Hourly demand = (hourly supply - transmission loss)
  2. Supply function is based on plant-level hourly cost data
  3. Demand is based on node-level hourly demand data
  4. Transmission capacity between regions:
     - Actual transmission capacity in each time period
     - Counterfactual: As if Chile did not integrate markets



The structural model solves this constrained optimization

$$\begin{aligned} & \underset{q_{it}\geq 0}{\text{Min}} \quad C_t = \sum_{i\in I} c_{it} q_{it}, \\ \text{s.t.} \quad & \sum_{i\in I} q_{it} - L_t = D_t, \quad q_{it} \leq k_i, \quad f_r \leq F_r. \end{aligned} \tag{1}$$

- Variables:
  - C_t: total system-wise generation cost at time $t \in T$
  - c_{it}: marginal cost of generation for plant $i \in I$ at time t
  - q_{it}: dispatched quantify of generation at plant i
  - L_t: Transmission loss of electricity
  - D_t: total demand
  - k_i: the plant's capacity of generation
  - f_r: inter-regional trade flow with transmission capacity F_r

Dynamic responses are solved as a zero-profit condition

$$E\left[\sum_{t\in T}\left(\frac{p_{it}(k_i)q_{it}(k_i)}{(1+r)^t}\right)\right]=\rho k_i \tag{2}$$

- where:
  - NPV of profit (left hand side) = Investment cost (right hand side)
  - ρ: solar investment cost per generation capacity (USD/MW)
  - k_i: generation capacity (MW) for plant i
  - p_{it}: market clearing price at time t
  - q_{it}: dispatched quantify of generation at plant i
  - r: discount rate
- This allows us to solve for the profitable level of entry for each scenario

We calibrate the model with detailed market data

- Network model
  - k-means clustering of province prices into 5 zones, observed flows between clusters to set transmission.
- Supply curve:
  - based on observed production and/or observed reported costs.
- Demand:
  - based on nodal level data, aggregated to clusters.
- Solar potential:
  - based on days without transmission congestion.
- Cost of solar:
  - based on zero profit condition.

The cost and benefit of the transmission investments

- Cost of the interconnection and reinforcement
  - $860 million and $1,000 million (Raby, 2016; Isa-Interchile, 2022)
- Benefit—we focus on three benefit measures
  - Changes in consumer surplus
  - Changes in net solar revenue (= revenue − investment cost)
  - Changes in environmental externalities

Cost-benefit results

Table: Cost-Benefit Analysis of Transmission Investments

	(1)	(2)
Modelling assumptions		
Investment effect due to lack of integration	No	Yes
Benefits from market integration (million USD/year)		
Savings in consumer cost	176.3	287.6
Savings in generation cost	73.4	218.7
Savings from reduced environmental externality	-161.4	249.4
Increase in solar revenue	110.7	183.5
Costs from market integration (million USD)		
Construction cost of transmission lines	1860	1860
Cost of additional solar investment	0	2522
Years to have benefits exceed costs		
With discount rate = 0	14.8	6.1
With discount rate = 5.83%	> 25	7.2
With discount rate = 10%	> 25	8.4
Internal rate of return		
Lifespan of transmission lines = 50 years	6.95%	19.67%
Lifespan of transmission lines = 100 years	7.23%	19.67%

Assessing the cost-benefit

- With the model, we can compute the benefits of the line, with and without investment effects.
- We find that investment effects are key to justify the cost of the line.
- The line was also very attractive from a consumer welfare perspective, even at 5.83% discount rate (Chile's official rate).
- Political economy makes renewable expansion "easy" in Chile.
- How to reduce political economy challenges in other jurisdictions?

Gowrisankaran, Langer, and Reguant (2024)

- Gowrisankaran, Langer, and Reguant (2024) quantify the interaction between regulatory distortions and the phase out of coal generators.
- **Question**: What is the scope for regulatory changes to speed-up phase-out of coal towards more efficient levels?
- **Tools**: structural model of regulatory distortions with dynamic investment.
- **Findings**:
  - We quantify that regulatory distortions delay coal phase-out.
  - Tweaking regulatory parameters has limited benefits compared to more direct policies (e.g., taxing carbon).

Conceptual Model of Regulatory Incentives

1. Regulator uses prudence standards to limit incentive for over-investment.
   - For coal, utility demonstrates prudence by using it to meet load.
   - This limits capital but doesn't fully correct the AJ incentive.
2. Utility still doesn't have the incentive to generate with the lowest cost technologies.
   - Regulator therefore sets a maximum rate of return that is decreasing with TVC.
   - Incentivize utility (but imperfectly) to use lowest cost technology.
3. If a new technology suddenly becomes available:
   - AJ incentive implies that utility keeps too much of the legacy technology.
   - Prudence incentive leads to over-use of the legacy technology.
   - This may slow an energy transition.

Model of Maximum Rate of Return and Rate Base

- In each year, y, regulator allows a maximum rate of return, $\bar{s}$, on the rate base, B, of:

$$\bar{s}_y = \left(\frac{TVC_y}{CostBasis} \right)^{-\gamma}$$

  - Incentivizes low costs for $\gamma > 0$.
  - *CostBasis*: observable fuel and import costs before the energy transition.
    - Used to capture unavoidable costs, such as transmission costs.
- The utility earns this rate of return on its rate base, B_y:

$$B_y = \alpha \left[K_y^{CCNG} + \alpha^{NGT} K_y^{NGT} + \alpha^{COAL} \left(\frac{exp(\mu_1 + \mu_2 U_y)}{1 + exp(\mu_1 + \mu_2 U_y)} \right) K_y^{COAL} \right].$$

  - We model coal usage $U_y = \overline{Q}^{COAL} / K^{COAL}$ as affecting the rate base.
- Regulator sets consumer rates such that $Revenues_y = TVC_y + \bar{s}_y \times B_y$.

Long-Run Retirement and Investment Decisions

- A utility facing this regulatory framework makes investment and retirement decisions every 3-year period, t, over 30 years, with 95% annual discount factor.
- Utilities choose coal retirement $x_t^{COAL} \leq 0$ and CCNG investment, $x_t^{CCNG} \geq 0$.
- Investment costs build on Ryan (2012) and Fowlie, Reguant, and Ryan (2016):

$$\delta_0^f \mathbb{1}\{x_t^f \neq 0\} + x_t^f(\delta_1^f + x_t^f \delta_2^f + \sigma^f \varepsilon_t^f).$$

- Unobservable component is on linear marginal cost term:
  - Allows for a non-singleton density of x_t^f (Kalouptsidi, 2018; Caoui, 2023).
  - Each ε_t^f is distributed standard normal and observed before the x_t^f choice.

State and Timing for Investment/Retirement Decisions

- Investment and retirement decisions depend on:
  1. Natural gas fuel price p_t^{NG}, which follows an exogenous AR(1) process.
  2. Coal and CCNG capacity, which evolve endogenously.
  3. Heat rates, coal fuel prices, demand, import supply curves, NGT capacity.
- Timing within each period is:
  1. Utility learns p_t^{NG} and makes its investment/retirement decisions
  2. Earns period profits, $\pi^*(K^{COAL}, K^{CCNG}, p^{NG})$ from operations decisions
  3. Realizes its retirements and investments

Hourly Operations Decisions

- Every hour, h, of year, y, the utility meets load with generation or imports:

$$\pi^*(K^{COAL}, K^{CCNG}, p^{NG}) = \max_{\vec{q}_y} \overbrace{\left(\frac{TVC(p^{NG}, \vec{q}_y)}{CostBasis}\right)^{-\gamma}}^{\text{Rate of return}} \overbrace{B(\vec{q}_y, K^{COAL}, K^{CCNG})}^{\text{Rate base}}$$

  - subject to meeting load and capacity constraints.

- Total variable costs TVC_y include import, fuel, startup/ramping, and O&M costs.
- Hours are connected via ramping costs, rate of return, and annual coal usage.
  - We solve for the optimum with a full-information finite horizon model.

Structural Estimation

1. Estimate import supply curves following Bushnell, Mansur, and Saravia (2008).
2. Estimate most structural parameters from utilities' hourly operations decisions:
   - Use indirect inference: GMM nested fixed-point approach
   - Finds parameters to match data correlations similar to reduced form evidence.
3. Estimate investment and retirement costs from dynamic decisions.
   - Also GMM full solution nested fixed-point approach.
   - Annual operating profits at each state are inputs to Bellman equation.
   - Moments capture differences between model and data investment/retirement.
   - Apply Gowrisankaran and Schmidt-Dengler (2024) algorithm:
     - Idea: find ε^f cutoffs for chosen investment levels while eliminating others.

Coefficient Estimates for Investment/Retirement Decisions

Parameter	Notation	Value	Std. Dev.
Fixed cost of coal retirement × 1e2	δ_0^{COAL}	-0.446	(9.79)
Linear coal cost per MW	δ_1^{COAL}	3.196	(0.44)
Quadratic coal cost per MW / 1e3	δ_2^{COAL}	0.117	(0.02)
Coal shock standard deviation per MW	σ^{COAL}	-0.430	(0.02)
Fixed cost of CCNG investment × 1e2	δ_0^{CCNG}	-0.509	(0.01)
Linear CCNG cost per MW	δ_1^{CCNG}	6.487	(0.08)
Quadratic CCNG cost per MW / 1e3	δ_2^{CCNG}	0.270	(0.05)
CCNG shock standard deviation per MW	σ^{CCNG}	-1.671	(0.06)

Note: All values in millions of 2006 dollars.

Counterfactuals examine value of regulatory changes

- Modifying the relevance of cost minimization incentives (γ, TVC penalty).
- Reducing the incentive to overutilize coal (μ_1, μ_2).

- Results:
  - Firms shift use between coal and gas.
  - Firms still maintain too much coal capacity and over-invest in gas, challenging the next energy transition.

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Tools today

- Model of electricity market
  - Static, long-run investment
  - Using mixed-integer programming tools in Julia
- Clustering to simplify data
  - To reduce problem size
  - Using k-means

Our example today

- Our example today will clear the market based on data from California (CAISO, see Reguant (2019)).
- We then need to solve for the objective function.

$$\begin{aligned} \max_q \quad & S(q) - C(q) \\ s.t. \quad & \text{demand=supply}, \\ & \text{other constraints.} \end{aligned}$$

- We solve for the quantities that maximize the gross surplus S minus the costs of generation C.
- Implicitly or explicitly, there is a price to electricity consumption.
- One can also clear for investment in the same optimization (social planner/competitive).

Solving the model with JuMP

- JuMP makes the formulation of electricity dispatch models relatively seamless.
- One code to express the model, one can then call several solvers depending on the needs.
- I will give you a "hint" of what JuMP can do.
- Example of highly configurable electricity expansion model based on Julia + JuMP:
  - https://github.com/GenXProject/GenX
  - https://netzeroamerica.princeton.edu/

Ingredients to a mathematical model

- Parameters/Inputs
- Variables
- Constraints
- Objective function
- Sense of the objective function
- The solver we want to use

Note: In mathematical programming, the terms 'variables' and 'parameters' are used the opposite way as in econometrics! Variables: what we are trying to solve. Parameters: what we already have, the inputs.

Solvers

- There is an array of optimization resources that are tailored to be particularly efficient in certain problems.
- Developed/used more in engineering and operations research.
- Examples:
  - Quadratic programs
  - Linear programs with integer variables
  - Nonlinear programs with integer variables
  - Programs with complementary conditions

Building blocks of the model

following Bushnell (2010)

- Model with perfect competition and free entry.
- Continuous investment in different technologies.
- Equivalent to least-cost social planner outcome.
- Entry of each technologies occurs until revenues of the marginal unit equal levelized costs of investment and operating costs.
- Assess long-run generation mix (coal, CCGT, peaking gas).
- Focus on thermal generation.

Model equations solution

The model equations are as follows

- **Demand** (we will assume this to be linear)

$$Q_t(p_t) = a_t - f(p_t)$$

- **Quantity**

$$q_{it} \geq 0 \perp p_t - c_i - \psi_{it} \leq 0 \quad \forall i, t$$

- **Shadow**

$$\psi_{it} \geq 0 \perp q_{it} - K_i \leq 0 \quad \forall i, t$$

- **Zero Profit**

$$K_i \geq 0 \perp F_i - \sum_t \psi_{it} \leq 0 \quad \forall i$$

The model is a complementarity problem. To solve these problems one can use special software or do it "brute force".

Complementary conditions formulation

- We can think of each complementarity condition as the product of two variables.
- We want to minimize the objective function and make sure it is zero subject to the constraints of z and w being non-negative:

$$\min z'w$$
$$\text{s.t. } z \geq 0, w \geq 0$$

- We need to check objective function is zero.
- Special solvers are tailored to solve these problems, such as PATH.

Mixed-integer programming

- We refer to mixed-integer programming for problems that have both discrete and continuous variables that we are trying to solve for.
- In the last 10-15 years, this type of problems has become easier to solve.
- Electricity markets are an important application, as there are many discrete decisions:
  - Should we use a power plant or not?
  - Is a technology "marginal" or not?
  - Is a transmission line at capacity or not?
  - For piece-wise linear functions, at which side of the function should we be?
  - Etc.

Mixed-integer formulation

- Mixed integer programs can be used very generally to express constraints or model discrete decisions.
- We can also use "tricks" to mimic Khun-Tucker conditions.
- For our complementarity-equivalent problem, we have:

$$z \geq 0, w \geq 0$$
$$z \leq M \cdot u, w \leq M \cdot (1 - u)$$

- u is a binary variable that sets condition on or off.
- Either z is zero or w is zero.
- M is a large number (convention to call it 'M', literally a big number).

Interested in these topics?

- See materials at `https://mreguant.github.io/em-course`.