

ACE Market Game Examples

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Outline

- ◆ ACE double-auction trading game
- ◆ An ACE two-sector trading game

EX 1: ACE Double-Auction Trading Game

- ◆ J. Nicolaisen, V. Petrov, L. Tesfatsion, *IEEE Transactions on Evolutionary Computation*, 5(5), 2001, pp. 504-523
<https://www2.econ.iastate.edu/tesfatsi/mpeieee.pdf>

◆ Key Issue Addressed:

Relative role of **structure vs. learning** in determining performance of a double-auction design for a day-ahead electricity market.

Key Issues We Address

* Sensitivity of market performance to changes in **market structure**:

RCON = Relative seller/buyer **concentration**

RCAP = Relative demand/supply **capacity**

* Sensitivity of market performance to changes in **trader learning**:

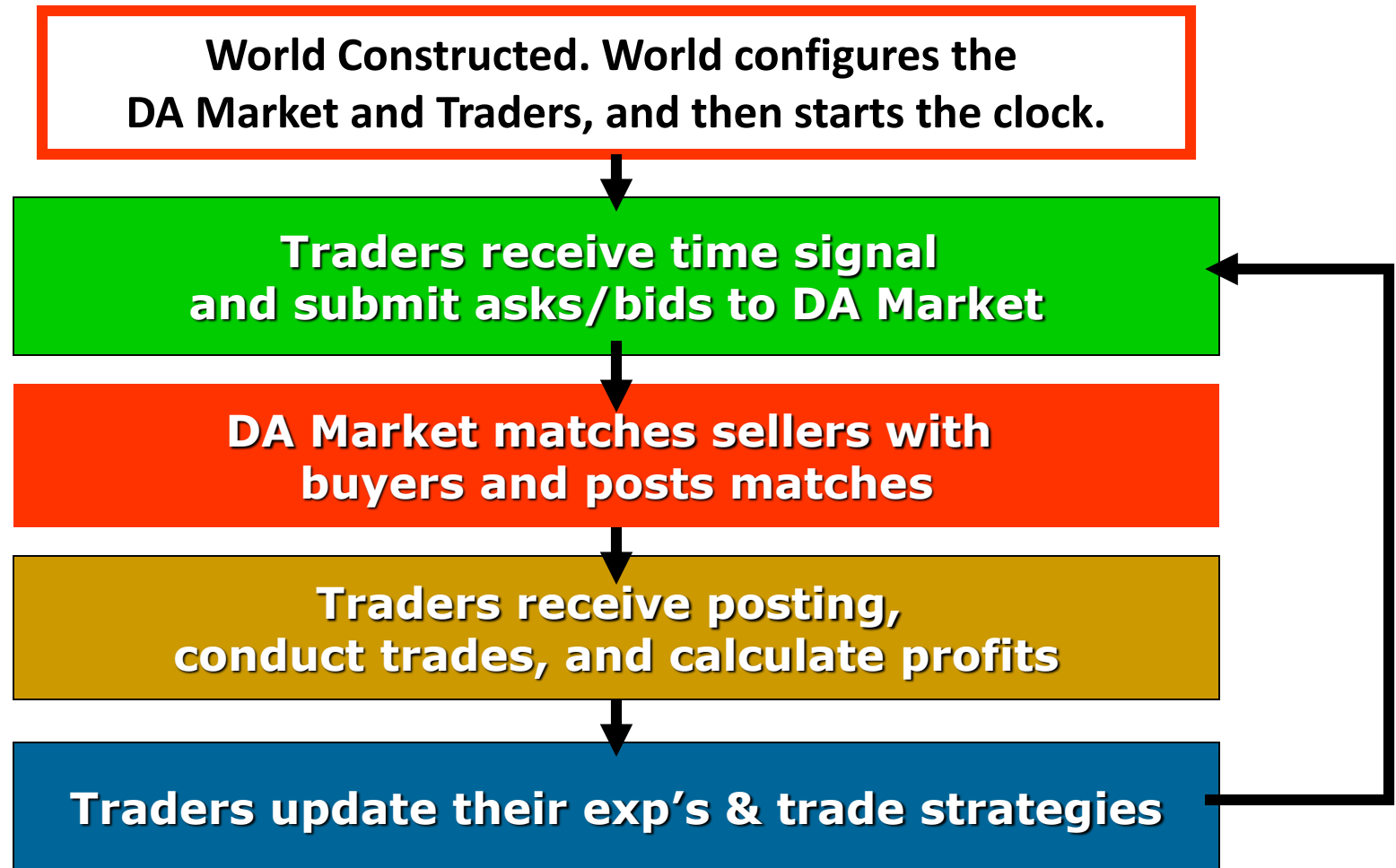
Individual learning via **Reinforcement Learning (RL)**

Social mimicry via **Genetic Algorithms (GAs)**

Market Performance Measures

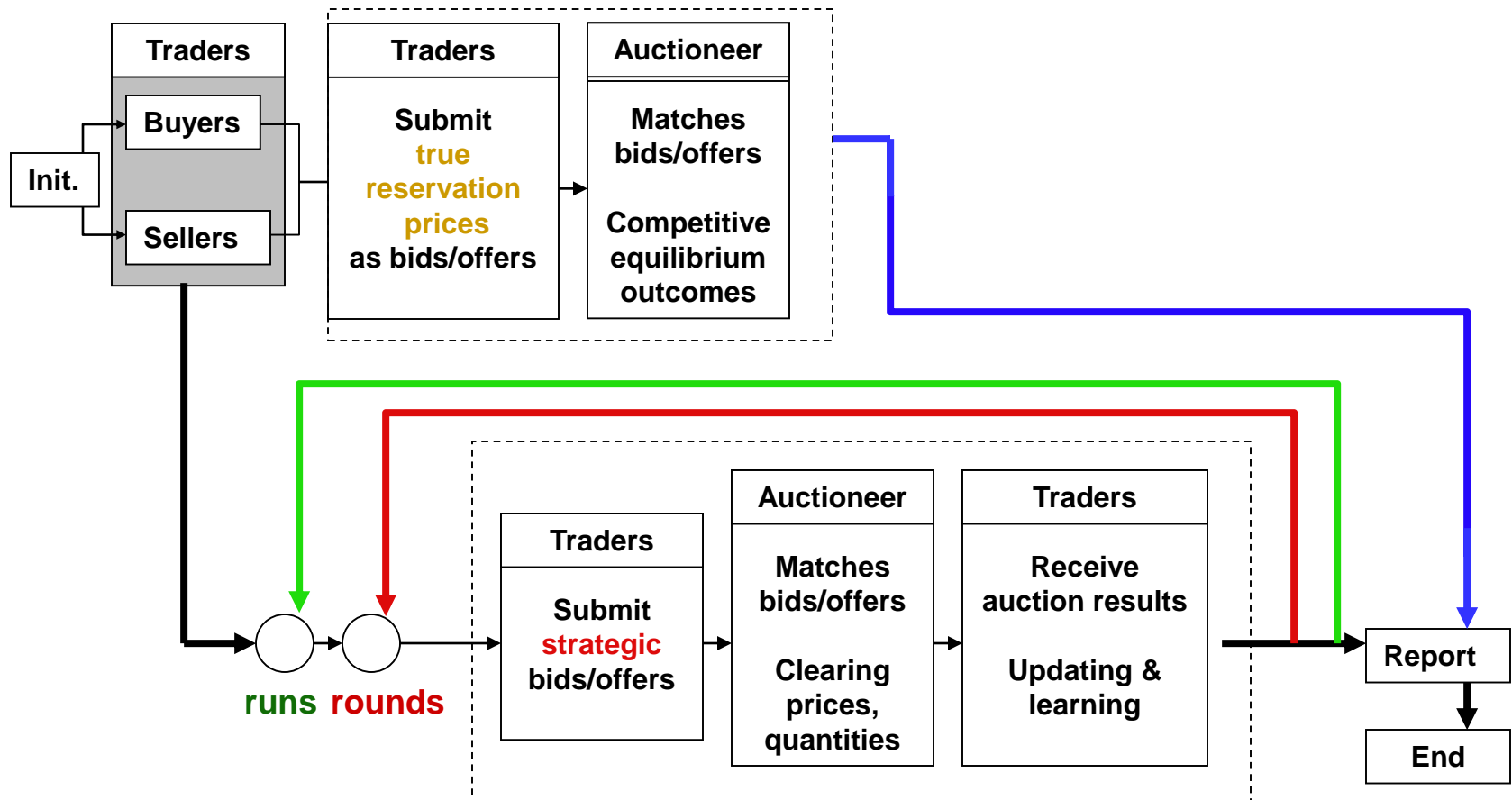
- ❑ **Market Efficiency:** Actual total net benefits extracted from the market relative to maximum possible total net benefits (competitive benchmark).
- ❑ **Market power:** The manner in which extracted total net benefits are distributed among the market participants.

Dynamic Flow of DA Market: Simple View



Dynamic Flow of DA Market: Detailed View

COMPETITIVE EQUILIBRIUM BENCHMARK CALCULATION (OFF-LINE)



Structural Treatment Factor Values

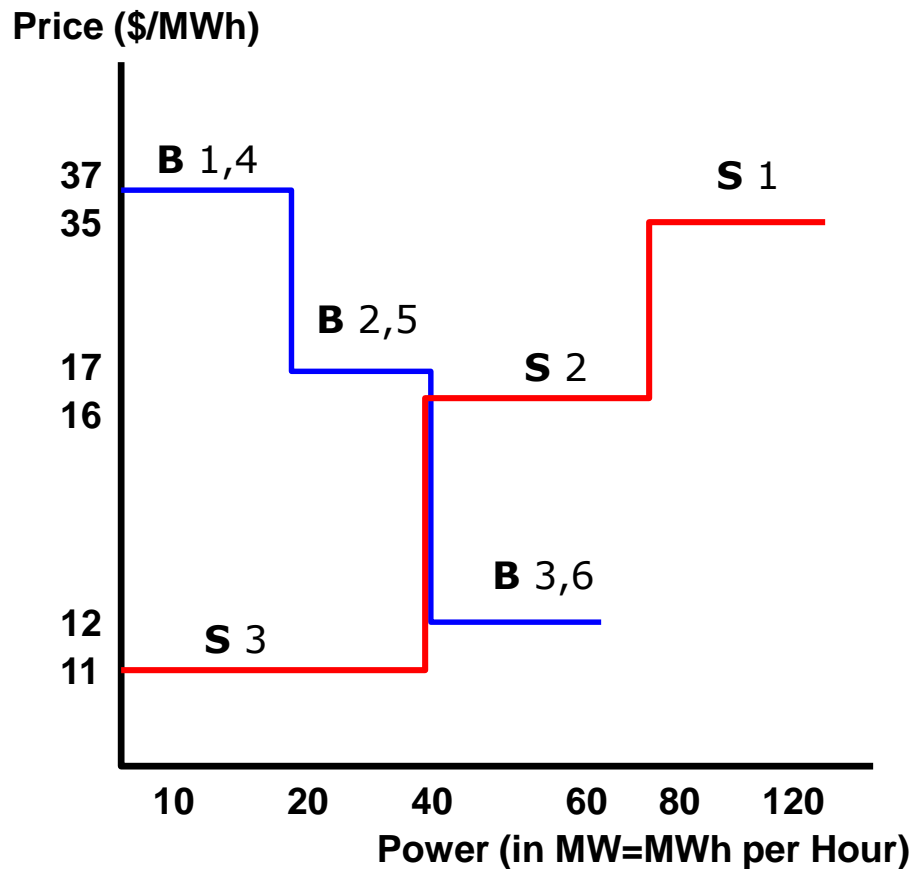
(tested for each learning treatment)

Ns = Number of Sellers
Nb = Number of Buyers
Cs = Seller Supply Capacity
Cb = Buyer Demand Capacity
RCON=N_s/N_b
RCAP=N_bC_b/N_sC_s

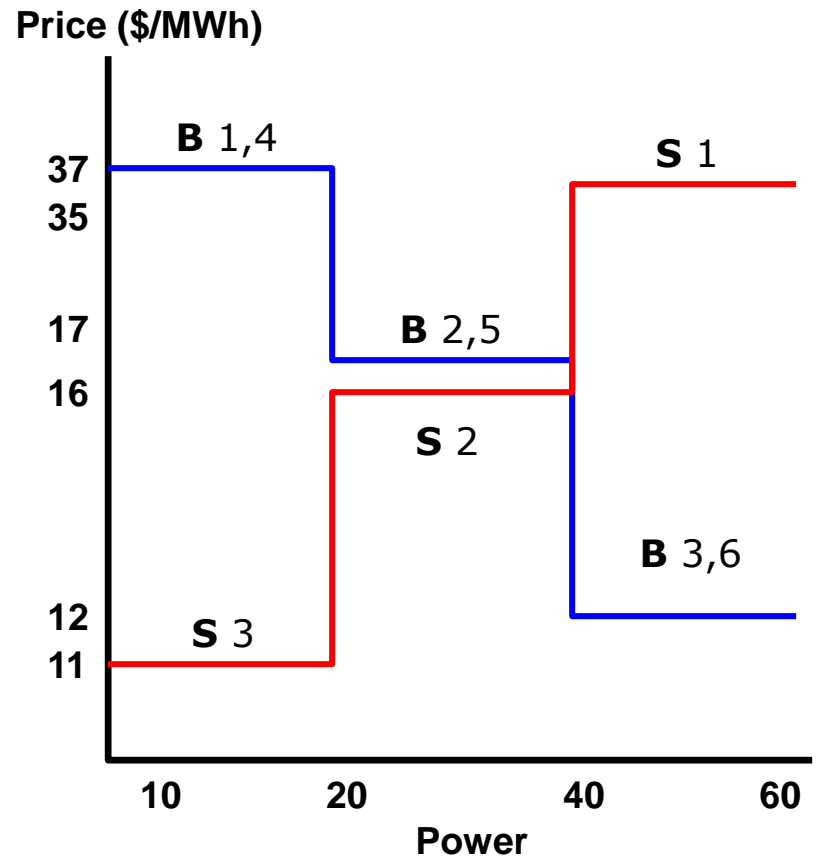
		RCAP		
		1/2	1	2
R C O N	2	Ns = 6 Nb = 3 Cs = 10 Cb = 10	Ns = 6 Nb = 3 Cs = 10 Cb = 20	Ns = 6 Nb = 3 Cs = 10 Cb = 40
	1	Ns = 3 Nb = 3 Cs = 20 Cb = 10	Ns = 3 Nb = 3 Cs = 10 Cb = 10	Ns = 3 Nb = 3 Cs = 10 Cb = 20
	1/2	Ns = 3 Nb = 6 Cs = 40 Cb = 10	Ns = 3 Nb = 6 Cs = 20 Cb = 10	Ns = 3 Nb = 6 Cs = 10 Cb = 10

True Total Demand and Supply Schedules (True Reservation Prices)

Cell (3,1)



Cell (3,2)



The Computational World

Public Access:

// **Public Methods**

The ***World Event Schedule***, i.e., a system clock that permits inhabitants to time and synchronize activities (e.g., submission of asks/bids into the DA market);
Protocols governing trader collusion;
Protocols governing trader insolvency;
Methods for receiving data;
Methods for retrieving World data.

Private Access:

// **Private Methods**

Methods for gathering, storing, and sending data;

// **Private Data**

World attributes (e.g., spatial configuration);
World inhabitants (DA market, buyers, sellers);
World inhabitants' methods and data.

The Computational DA Market

Public Access:

// **Public Methods**

getWorldEventSchedule(clock time);

Protocols governing the public posting of bids/offers;

Protocols governing matching, trades, and settlements;

Methods for receiving data;

Methods for retrieving Market data.

Private Access:

// **Private Methods**

Methods for gathering, storing, and sending data.

// **Private Data**

Data recorded about sellers (e.g., seller offers);

Data recorded about buyers (e.g., buyer bids);

Address book (communication links).

A Computational DA Trader

Public Access:

// **Public Methods**

getWorldEventSchedule(clock time);
getWorldProtocols (collusion, insolvency);
getMarketProtocols (posting, matching, trade, settlement);
Methods for receiving data;
Methods for retrieving Trader data.

Private Access:

// **Private Methods**

Methods for gathering, storing, and sending data;
Methods for calculating expected & actual profit outcomes;
Method for updating my bid/offer strategy (**LEARNING**).

// **Private Data**

Data about me (history, profit function, current wealth,...);
Data about external world (rivals' bids/offers, ...);
Address book (communication links).

What Do DA Traders Learn?

Supply Offers and Demand Bids

- **Offer for each Seller i** = *reported* supply q_i^S of real power in Mega-Watts (MWs) together with a *reported* unit (i.e., per-MW) price p_i in dollars \$ per MW
- **Bid for each Buyer j** = *reported* demand q_j^D for real power in MWs together with a *reported* unit price p_j in \$ per MW
- *Action choices for sellers* = Their possible OFFERS
- *Action choices for buyers* = Their possible BIDS

How Might DA Traders Learn?

❑ One possibility:

Reactive Reinforcement Learning (RL)

Asks....

Given *past* events, what action
should I take *now* ?

Examples:

Three-parameter RL based on human-subject experiments (Roth-Erev, 1995, 1998),
Modified Roth-Erev RL for electricity double auctions (Nicolaisen, Petrov, Tesfatsion,
IEEE TEC, 2001)

How Might DA Traders Learn...

- Another possibility:

Anticipatory Learning

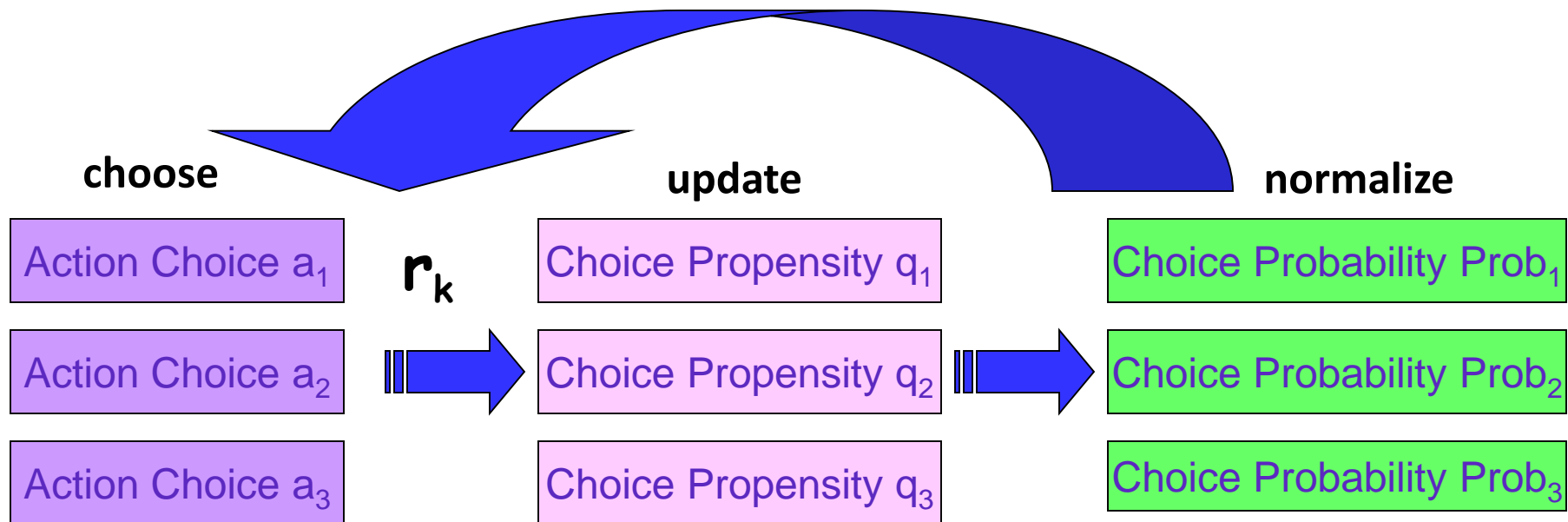
Asks....

If I take this action ***now***, what will
happen in the ***future*** ?

Examples: Q-Learning (Watkins, 1989); Temporal-Difference Reinforcement Learning (Sutton/Barto, 1998)

Learning Method Used for This study: MRE Reactive Reinforcement Learning

(MRE = Modified Roth-Erev, see Nicolaisen et al., 2001)



- ❑ Each trader maintains action choice propensities q , normalized to action choice probabilities Prob, to choose actions. A good (bad) profit r_k for action a_k results in a strengthening (weakening) of the propensity q_k for a_k .

MRE RL = Modified Roth-Erev Reinforcement Learning

1. **Initialize** action propensities to an initial propensity value.
2. **Generate** choice probabilities for all actions using current propensities.
3. **Choose** an action according to the current choice probability distribution.
4. **Update** propensities for all actions using the reward for the last chosen action.
5. **Repeat** from step 2.

MRE RL: Updating of Action Propensities

Parameters:

- $q_j(1)$ Initial propensity
- ϵ Experimentation
- ϕ Recency (forgetting)

Variables:

- a_j Current action choice
- q_j Propensity for action a_j
- a_k Last action chosen
- r_k Reward for action a_k
- t Current time step
- N Number of actions

$$q_j(t + 1) = [1 - \phi]q_j(t) + E_j(\epsilon, N, k, t)$$

$$E_j(\epsilon, N, k, t) = \begin{cases} r_k(t)[1 - \epsilon] & \text{if } j = k \\ q_j(t) \frac{\epsilon}{N-1} & \text{if } j \neq k \end{cases}$$

From Propensities to Probabilities for MRE RL

$$p_j(t) = \frac{q_j(t)}{\sum_{j=0}^{N-1} q_j(t)}$$

$p_j(t)$ = Probability of choosing action j at time t

N = Number of available actions at each time t

Sample Table of Experimental Results

TABLE VI
EXPERIMENTAL MARKET POWER AND EFFICIENCY OUTCOMES FOR THE BEST FIT MRE ALGORITHM WITH 1000 AUCTION ROUNDS AND PARAMETER VALUES
 $s(1) = 9.00$, $r = 0.10$, AND $c = 0.20$

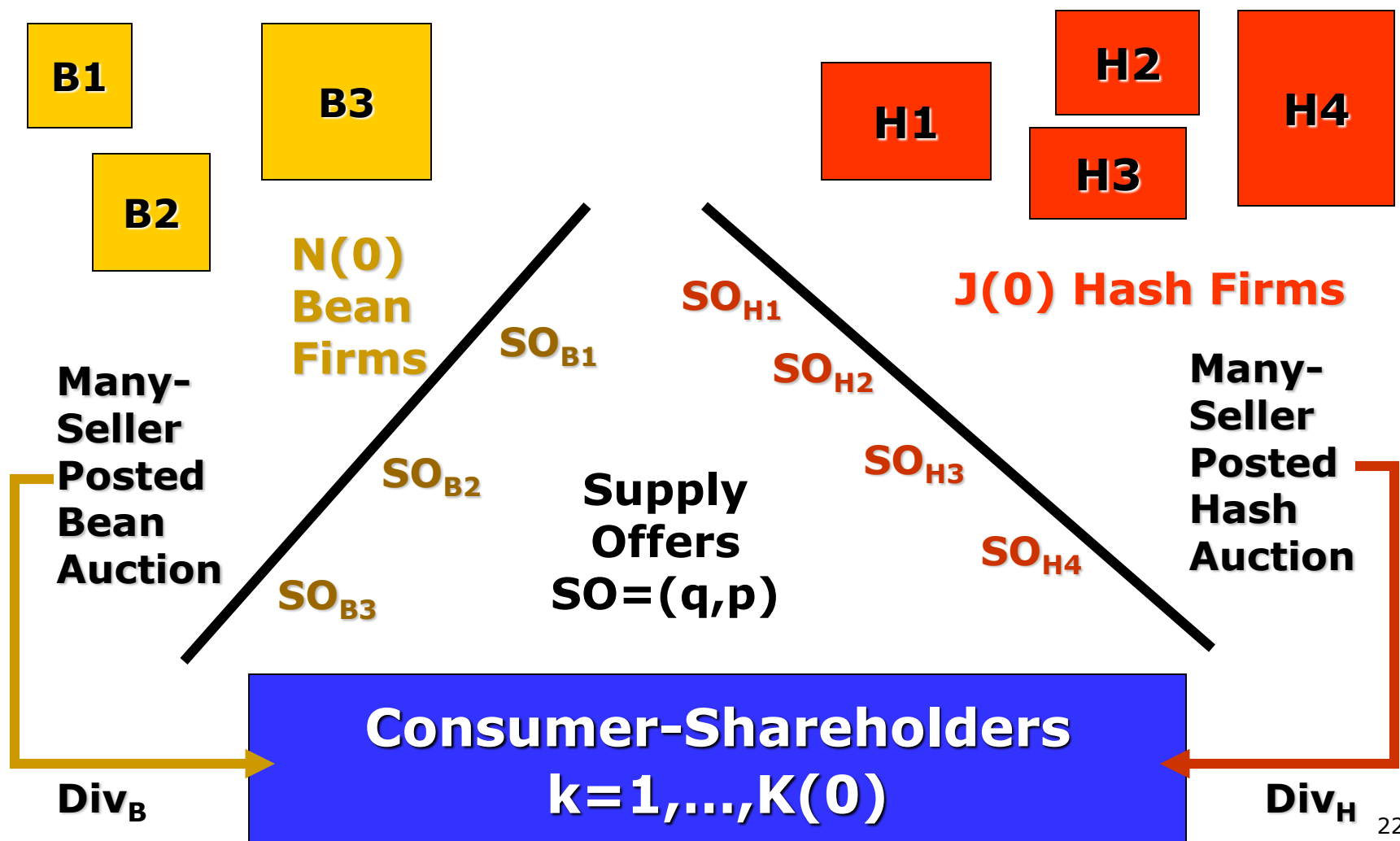
	1/2		Relative Capacity 1		2	
	MP	StdDev	MP	StdDev	MP	StdDev
2	All Buyers: -0.13*	(0.09)	All Buyers: -0.15*	(0.09)	All Buyers: 0.10	(0.30)
	All Sellers: 0.55*	(0.38)	All Sellers: 0.38*	(0.33)	All Sellers: -0.10	(0.25)
	Buyer[1]: -0.12*	(0.08)	Buyer[1]: -0.13*	(0.10)	Buyer[1]: 0.10	(0.30)
	Buyer[2]: -0.20	(0.40)	Buyer[2]: -0.75*	(0.33)	Buyer[2]: ZP	(0.00)
	Buyer[3]: ZP	(0.00)	Buyer[3]: ZP	(0.00)	Buyer[3]: ZP	(0.00)
	Seller[1]: ZP	(0.00)	Seller[1]: ZP	(0.00)	Seller[1]: ZP	(0.00)
	Seller[2]: ZP	(0.00)	Seller[2]: -0.50	(1.34)	Seller[2]: -0.12	(0.34)
	Seller[3]: 0.54	(0.63)	Seller[3]: 0.45*	(0.40)	Seller[3]: -0.10	(0.22)
	Seller[4]: ZP	(0.00)	Seller[4]: ZP	(0.00)	Seller[4]: ZP	(0.00)
	Seller[5]: ZP	(0.00)	Seller[5]: -0.42	(1.67)	Seller[5]: -0.08	(0.36)
	Seller[6]: 0.55	(0.60)	Seller[6]: 0.46*	(0.41)	Seller[6]: -0.09	(0.24)
	Efficiency: 99.81	(0.02)	Efficiency: 96.30	(0.05)	Efficiency: 99.88	(0.06)
Relative Concentration 1	MP	StdDev	MP	StdDev	MP	StdDev
	All Buyers: -0.22*	(0.12)	All Buyers: -0.13*	(0.10)	All Buyers: 0.13	(0.33)
	All Sellers: 0.80*	(0.53)	All Sellers: 0.28	(0.35)	All Sellers: -0.10	(0.26)
	Buyer[1]: -0.21*	(0.11)	Buyer[1]: -0.11*	(0.10)	Buyer[1]: 0.13	(0.33)
	Buyer[2]: -0.31	(0.44)	Buyer[2]: -0.80*	(0.40)	Buyer[2]: ZP	(0.00)
	Buyer[3]: ZP	(0.00)	Buyer[3]: ZP	(0.00)	Buyer[3]: ZP	(0.00)
	Seller[1]: ZP	(0.00)	Seller[1]: ZP	(0.00)	Seller[1]: ZP	(0.00)
	Seller[2]: ZP	(0.00)	Seller[2]: -0.37	(1.89)	Seller[2]: -0.10	(0.34)
	Seller[3]: 0.76*	(0.63)	Seller[3]: 0.34	(0.45)	Seller[3]: -0.11	(0.24)
	Efficiency: 92.13	(0.09)	Efficiency: 94.59	(0.07)	Efficiency: 100.00	(0.00)
1/2	MP	StdDev	MP	StdDev	MP	StdDev
	All Buyers: -0.21*	(0.12)	All Buyers: -0.14*	(0.08)	All Buyers: 0.09	(0.24)
	All Sellers: 0.67*	(0.46)	All Sellers: 0.30	(0.31)	All Sellers: -0.07	(0.19)
	Buyer[1]: -0.18*	(0.12)	Buyer[1]: -0.14*	(0.10)	Buyer[1]: 0.09	(0.27)
	Buyer[2]: -0.37	(0.47)	Buyer[2]: -0.77*	(0.44)	Buyer[2]: ZP	(0.00)
	Buyer[3]: ZP	(0.00)	Buyer[3]: ZP	(0.00)	Buyer[3]: ZP	(0.00)
	Buyer[4]: -0.20*	(0.11)	Buyer[4]: -0.11	(0.11)	Buyer[4]: 0.10	(0.25)
	Buyer[5]: -0.38	(0.47)	Buyer[5]: -0.73*	(0.46)	Buyer[5]: ZP	(0.00)
	Buyer[6]: ZP	(0.00)	Buyer[6]: ZP	(0.00)	Buyer[6]: ZP	(0.00)
	Seller[1]: ZP	(0.00)	Seller[1]: ZP	(0.00)	Seller[1]: ZP	(0.00)
	Seller[2]: ZP	(0.00)	Seller[2]: 0.14	(2.69)	Seller[2]: -0.08	(0.27)
	Seller[3]: 0.63*	(0.55)	Seller[3]: 0.32	(0.48)	Seller[3]: -0.07	(0.17)
	Efficiency: 91.84	(0.09)	Efficiency: 94.24	(0.07)	Efficiency: 100.00	(0.00)

ZP indicates that zero profits were earned both in the auction and in competitive equilibrium.

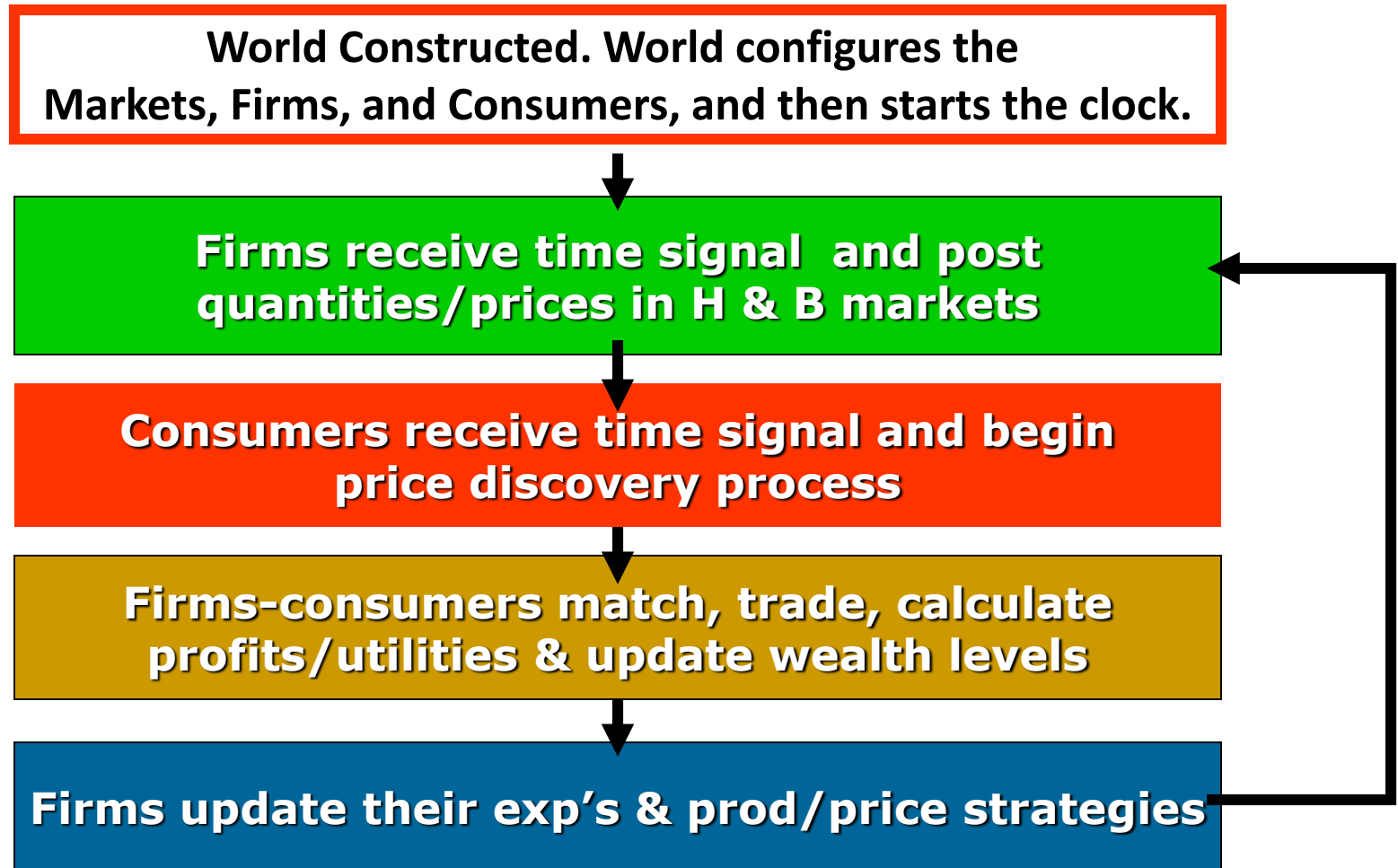
Summary of Policy-Relevant DA Findings

- **Market Efficiency:** Generally high when traders use MRE (Modified Roth-Erev) reinforcement learning **but not** when traders use GA (genetic algorithm) social mimicry (*type of learning can matter*).
- **Structural Market Power:** Microstructure of the DA market is strongly predictive for the relative market power of traders (*rule details matter*).
- **Strategic Market Power:** Traders are **not** able to change their relative market power through learning (*the importance of countervailing power*).

Example 2: An ACE Bilateral Trade Hash-and-Beans Economy



Dynamic Flow of ACE H&B Economy



Dynamic Flow of Activity for H & B Firms

- ◆ Each firm f starts out ($T=0$) with *money* $M_f(0)$ and a *production capacity* $Cap_f(0)$
- ◆ Firm f 's *fixed cost* $FC_f(T)$ in each $T \geq 0$ is proportional to its *current capacity* $Cap_f(T)$
- ◆ At beginning of each $T \geq 0$, firm f selects a *supply offer* = *(production level, unit price)*
- ◆ At end of $T \geq 0$, firm f is *solvent* if it has a *NetWorth*(T) =:
 $[Profit(T) + M_f(T) + ValCap_f(T)] > 0$
- ◆ If solvent, firm f allocates its *profits (+ or -)* between M_f , CAP_f , and dividend payments.

Dynamic Flow of Activity for Consumer-Shareholders

- ◆ Each consumer k starts out ($T=0$) with a *lifetime money endowment profile*

$$(Mk_{youth}, Mk_{middle}, Mk_{old})$$

- ◆ In each $T \geq 0$, consumer k 's *utility* is measured by

$$U_k(T) = (\text{hash}(T) - h_k^*)^{\alpha_k} \cdot (\text{beans}(T) - b_k^*)^{[1-\alpha_k]}$$

- ◆ In each $T \geq 0$, consumer k seeks to secure maximum utility by **searching** for beans and hash to buy at **lowest possible prices**.
- ◆ At end of each $T \geq 0$, consumer k **dies** unless consumption meets *subsistence needs*

$$(b_k^*, h_k^*).$$

Experimental Design Treatment Factors

- ◆ **Initial size of consumer sector** [$K(0)$]
- ◆ **Initial concentration** [$N(0)$, $J(0)$, $\text{Cap}(0)$ values]
- ◆ **Firm learning** (supply offers & profit allocations)
- ◆ **Firm cost functions**
- ◆ **Firm initial money holdings** [$M_f(0)$]
- ◆ **Firm rationing protocols** (for excess demand)
- ◆ **Consumer price discovery processes**
- ◆ **Consumer money endowment profiles**
(rich, poor, \nearrow , \searrow , life cycle u-shape)
- ◆ **Consumer preferences** (θ values)
- ◆ **Consumer subsistence needs** (b^* , h^*)

The Computational World

Public Access:

// **Public Methods**

The ***World Event Schedule***, i.e., a system clock that permits inhabitants to time and synchronize activities (e.g., opening/closing of H & B markets);

Protocols governing firm collusion;

Protocols governing firm insolvency;

Methods for receiving data;

Methods for retrieving World data.

Private Access:

// **Private Methods**

Methods for gathering, storing, and sending data;

// **Private Data**

World attributes (e.g., spatial configuration);

World inhabitants (H & B markets, firms, consumers);

World inhabitants' methods and data.

A Computational Market

Public Access:

// **Public Methods**

getWorldEventSchedule(clock time);

Protocols governing the public posting of supply offers;

Protocols governing matching, trades, and settlements;

Methods for receiving data;

Methods for retrieving Market data.

Private Access:

// **Private Methods**

Methods for gathering, storing, and sending data.

// **Private Data**

Data recorded about firms (e.g., sales);

Data recorded about consumers (e.g., purchases);

Address book (communication links).

A Computational Consumer

Public Access:

// **Public Methods**

getWorldEventSchedule(clock time);
getWorldProtocols (stock share ownership);
getMarketProtocols (price discovery process, trade process);
Methods for receiving data;
Methods for retrieving stored Consumer data.

Private Access:

// **Private Methods**

Methods for gathering, storing, and sending data;
Method for determining my budget constraint;
Method for searching for lowest prices.

// **Private Data**

Data about me (history, utility function, current wealth,...);
Data about external world (posted supply offers, ...);
Address book (communication links).

A Computational Firm

Public Access:

// **Public Methods**

getWorldEventSchedule(clock time);
getWorldProtocols (collusion, insolvency);
getMarketProtocols (posting, matching, trade, settlement);
Methods for receiving data;
Methods for retrieving Firm data.

Private Access:

// **Private Methods**

Methods for gathering, storing, and sending data;
Methods for calculating expected & actual profit outcomes;
Method for allocating my profits to my shareholders;
Method for updating my supply offers (**LEARNING**).

// **Private Data**

Data about me (history, profit function, current wealth,...);
Data about external world (rivals' supply offers, ...);
Address book (communication links).

Interesting Issues for Exploration

- ◆ Initial conditions → **carrying capacity?**
(Survival of firms/consumers in long run)
- ◆ Initial conditions → **market clearing?**
(Walrasian equilibrium benchmark)
- ◆ Initial conditions → **market efficiency?**
(Walrasian equilibrium benchmark)
- ◆ Standard concentration measures at $T=0$ →
good predictors of long-run market power?
- ◆ Importance for market performance of **trader learning abilities vs. market structure ?** (*Gode/Sunder, JPE, 1993*)

ACE Hash-and-Beans Economy: Comp Lab Implementation

Christopher Cook and Leigh Tesfatsion, “**Agent-Based Computational Laboratory for the Experimental Study of Complex Economic Systems**”

- ◆ Computational laboratory under construction for the ACE Hash-and-Beans Economy
- ◆ Programming language C#/.Net (all WinDesktops)
- ◆ Under development for Econ 308 (ACE course)
<https://www2.econ.iastate.edu/classes/econ308/tesfatsion/>

ACE Hash & Beans Economy: Comp Lab Main Screen

Form1
File Tools Window Help

Untitled 1 (Empty Lab)

Hash & Bean Multi-Market Economy Model

CONSUMERS	Group	Count
	Cons Type 1	100
	Cons Type 2	100
	Total:	200

Consumer Details

Group Name: Consumption Needs: Hash: Beans: Endowment Schedule: Lifecycle [\[edit\]](#)

Count: Initial:

Preference: [\[edit\]](#)
 $\alpha = 0.505$ Slightly Prefers Hash

FIRMS	Group	Count
	Large	1 1
	Small	20 20
	Total:	21 21

Firm Details

Group Name: Initial Assets: Money: Capacity: Cost Function: Default [\[edit\]](#)

Hash Firms: Bean Firms:

Profit Distribution: Money: Dividends: Learning Strategy: Random P & Q (Def) [\[edit\]](#)

Experiment Number: Trial Count: Trial Length (TMax):

START