Dynamic Decision Making Workshop

Incentives for Discovery in Computationally Hard Environments

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Intellectual discovery is combinatorial in nature
→ Search is costly
Romer (1990); Romer (1993)

An ideal institution must solve two problems
→ Induce sufficient incentive for costly search
→ Coordinate search across agents

Hayek (1945): Markets are effective **coordinators**
Nuvolari (2004); Bossaerts, et al., (2024); Bossaerts, et al., (in prep)

This paper: markets as an incentive mechanism for intellectual discovery.

Operationalising intellectual discovery

What kind of task is suitable?
⟶ Mirror the **combinatorial** nature of discovery
⟶ **Canonical**, with a well-defined optimum
⟶ Enables precise **control of difficulty**

Our choice: **0-1 Knapsack Problem (KP)**

INPUT

weights: $W = \{w_1, \ldots, w_n\}$
values: $V = \{v_1, \ldots, v_n\}$
capacity: C

⟶

OBJECTIVE

$$\max_X \sum_{i=1}^{n} v_i x_i \quad s.t. \quad \sum_{i=1}^{n} w_i x_i \leq C$$

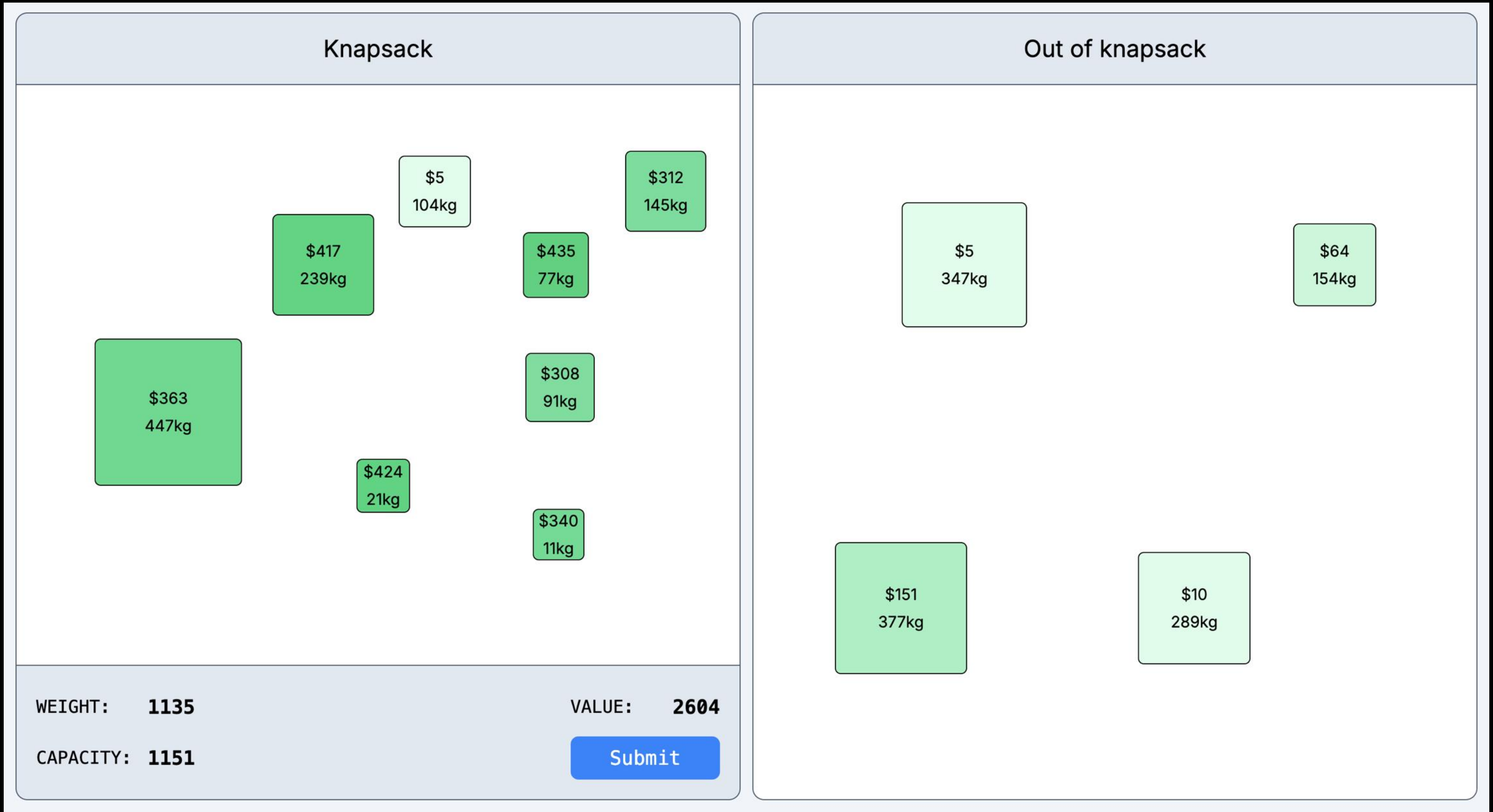
$$x_i \in \{0, 1\}$$

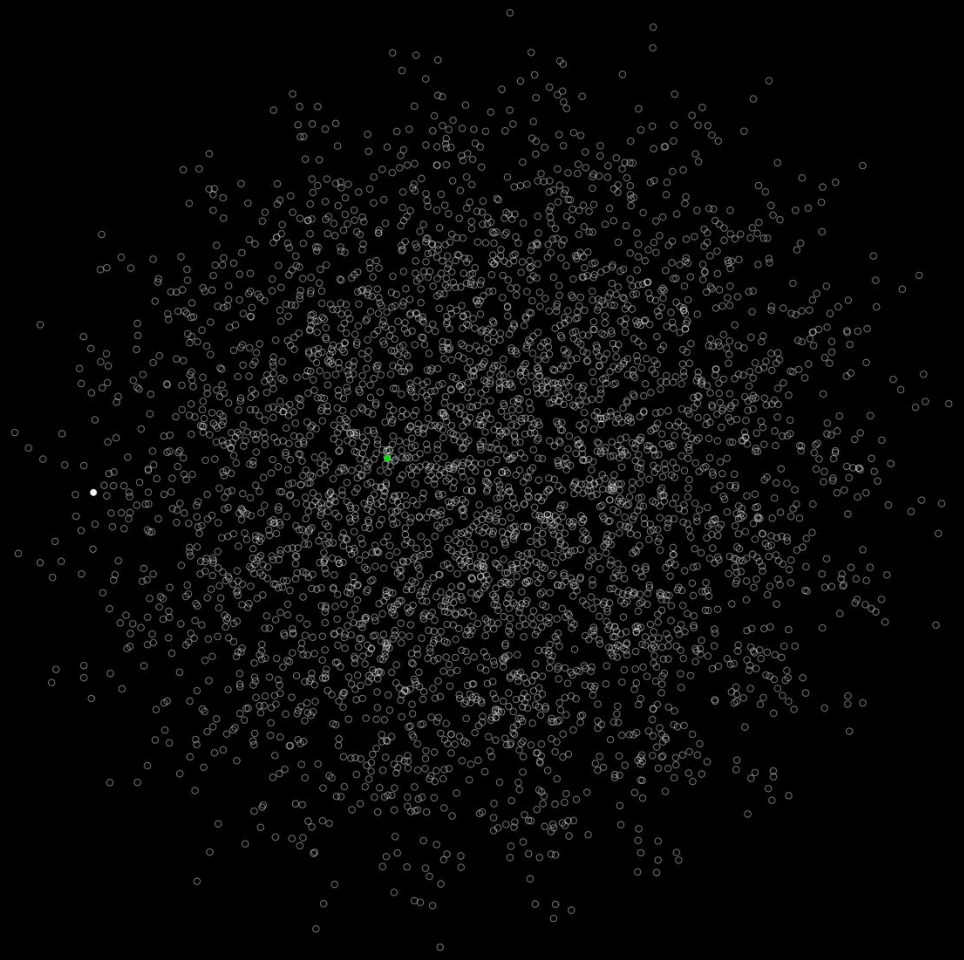
⟶

OUTPUT

$$X = \{x_1, \ldots, x_n\},\ x_i \in \{0, 1\}$$

Knapsack problem





Problem: The total solution space is too vast to exhaustively explore.

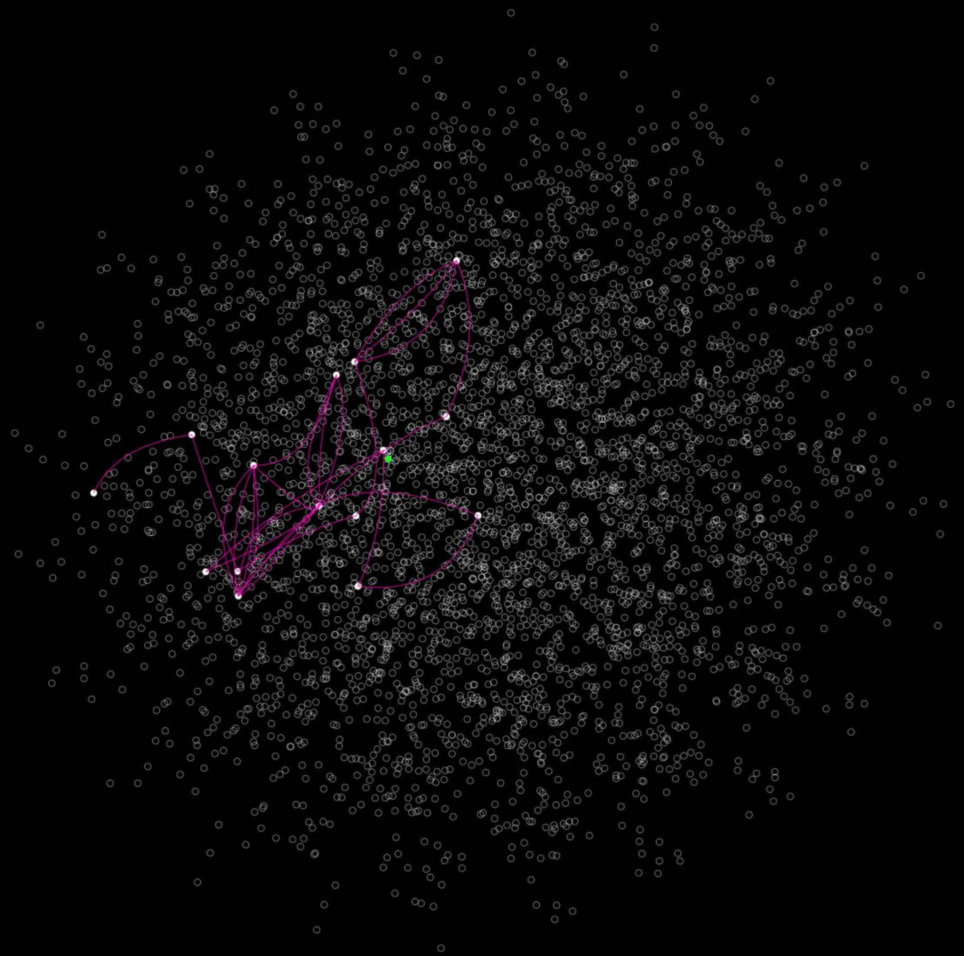
Compromise: Individuals try to strike a balance between:

→ **Solution quality:** the resulting solution should be within ϵ of the optimum.

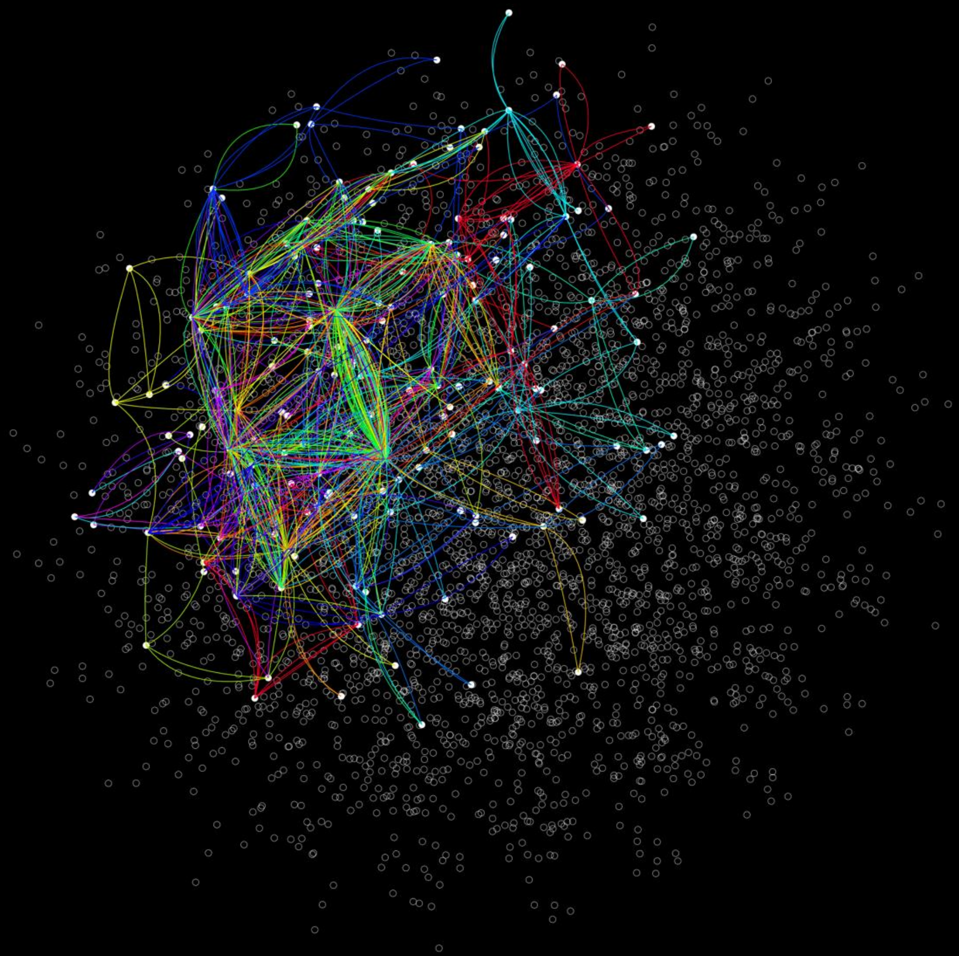
→ **Frugality:** computational cost should be minimised.

Result: Search over constrained subset of total solution space.

Collective problem-solving



A single individual explores a small subset of the solution space.



A **group of individuals** collectively explore a large portion of the solution space.

N = 120 participants from the University of Melbourne community.

Solve 10 instances of the Knapsack Problem (KP)

Three treatments (within-subject)
→ **Market**: Market-based (indirect) incentives (M)
→ **Individual**: Proportional payments (PP)
→ **Ideal**: Proportional payments + signal (PP + S)

Two levels of problem difficulty (easy, and hard)
→ Five **easy** instances of the KP
→ Five **hard** instances of the KP

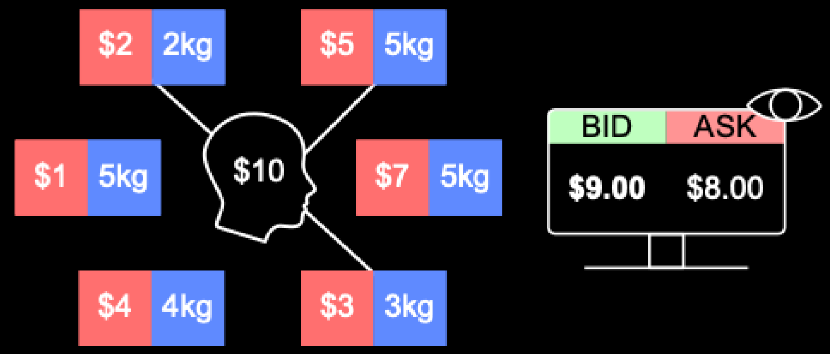
Block structure

Block	N	Session 1	Session 2	Session 3
1	21	PP	PP + S	M
2	21	PP	M	PP + S
3	19	PP + S	PP	M
4	18	PP + S	M	PP
5	21	M	PP + S	PP
6	20	M	PP	PP + S

Order of treatment conditions. Sessions were held on one week apart, on the same day of the week, at the same time.

Markets[1]

→ Participants solve the problem while trading experimental assets ("stocks")
→ The stock promises an end-of-period dividend equal to the highest solution discovered by anyone
→ Indirect incentive to solve the KP:



Profit comes from

→ Buying stocks at prices below the final best solution, and
→ Selling stocks at prices above the final best solution.

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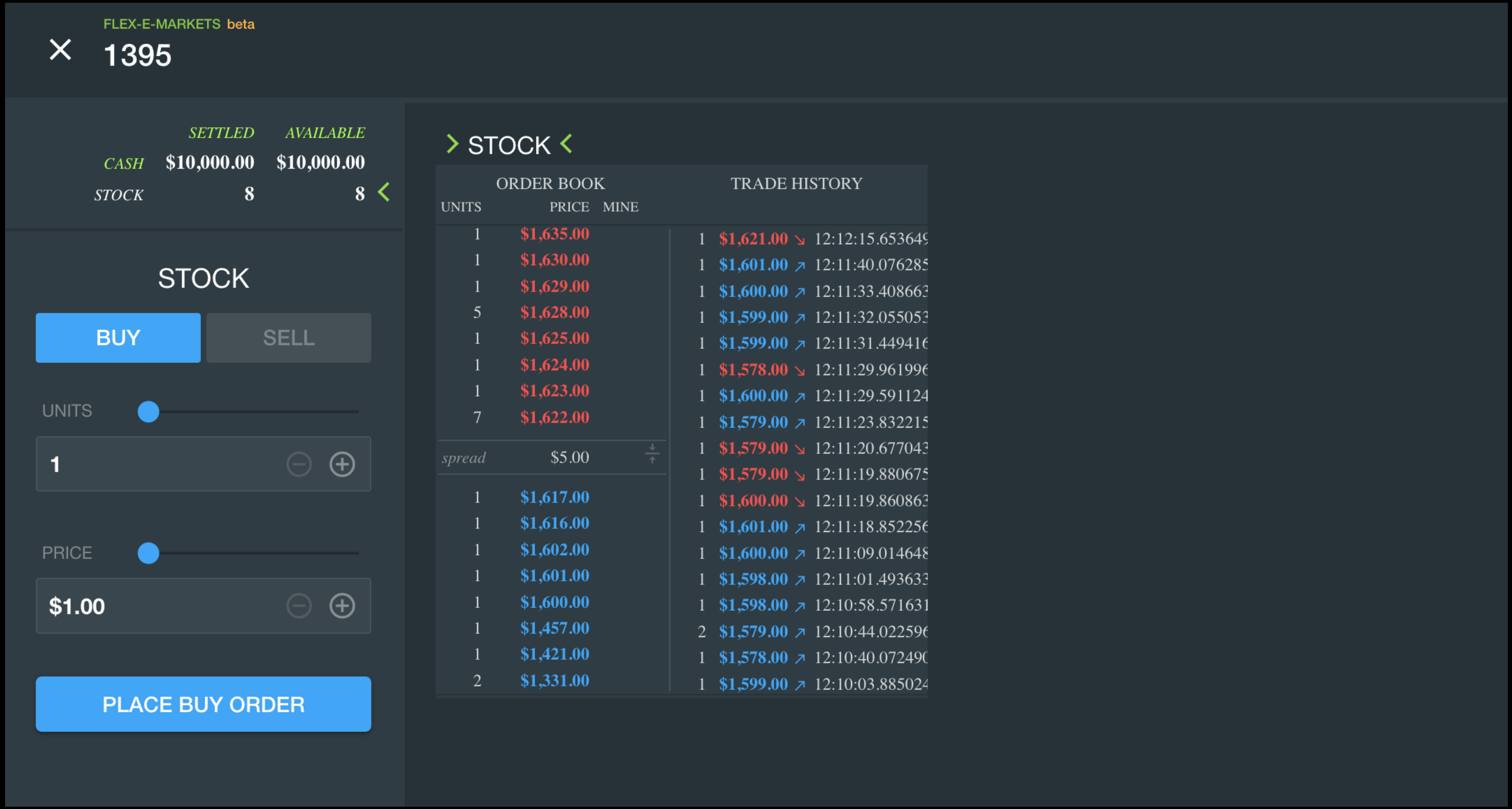
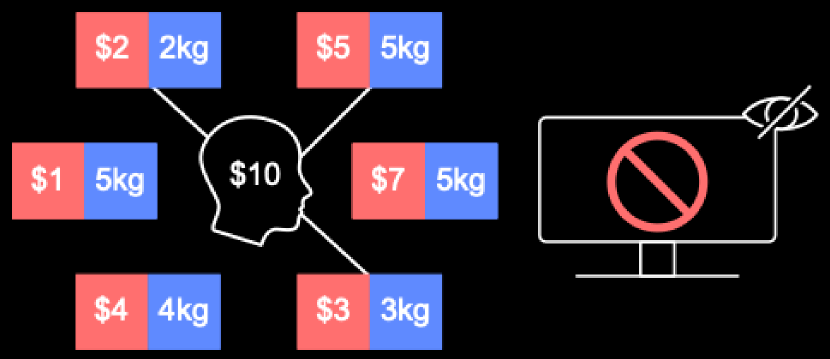
1. Adapted from experiment two in Bossaerts, Peter, et al. "Resource allocation, computational complexity, and market design." Journal of Behavioral and Experimental Finance 42 (2024): 100906.

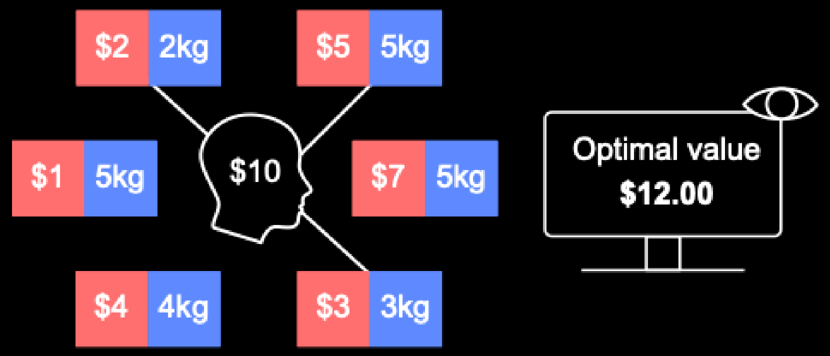
Trading interface (Flex-e-markets)



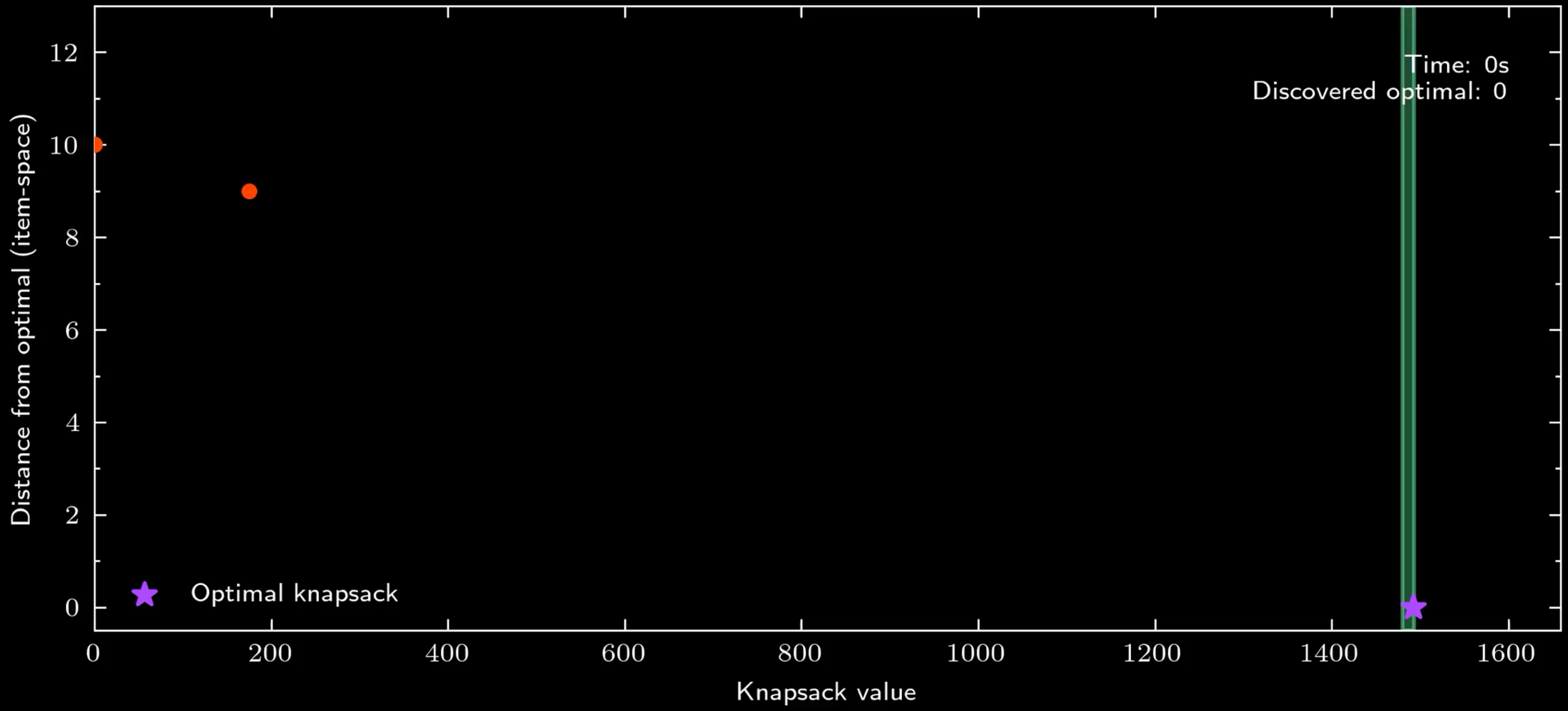
Proportional payments (PP)
→ Paid in proportion to own performance
→ $1.50 in proportion to submitted value
→ $1.50 bonus for finding the optimal solution
→ Direct incentive to solve the KP



Proportional payments + signal (PP+S)
→ Identical incentives to PP
→ Optimal value revealed to participants before commencing search



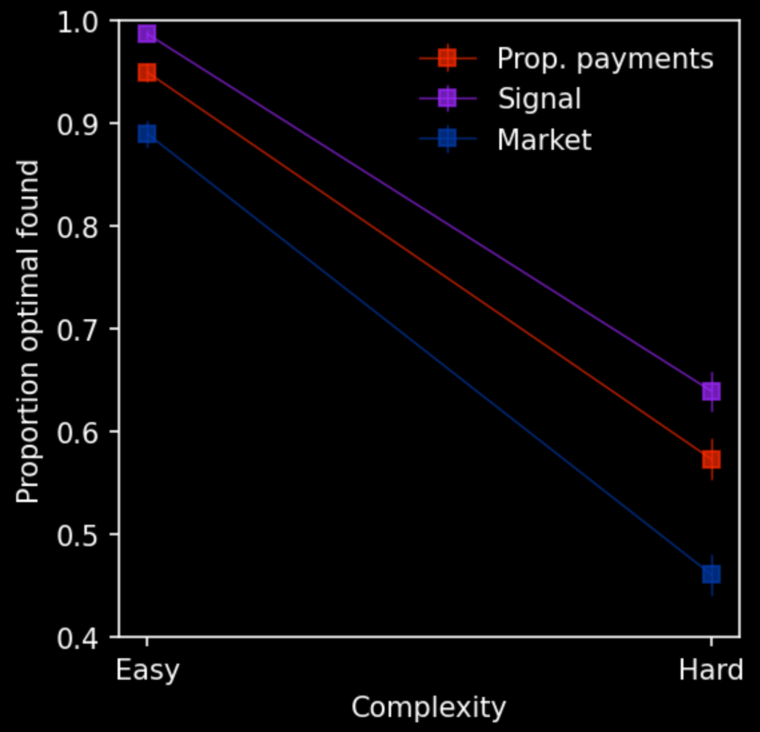
Market condition



Outcome measures

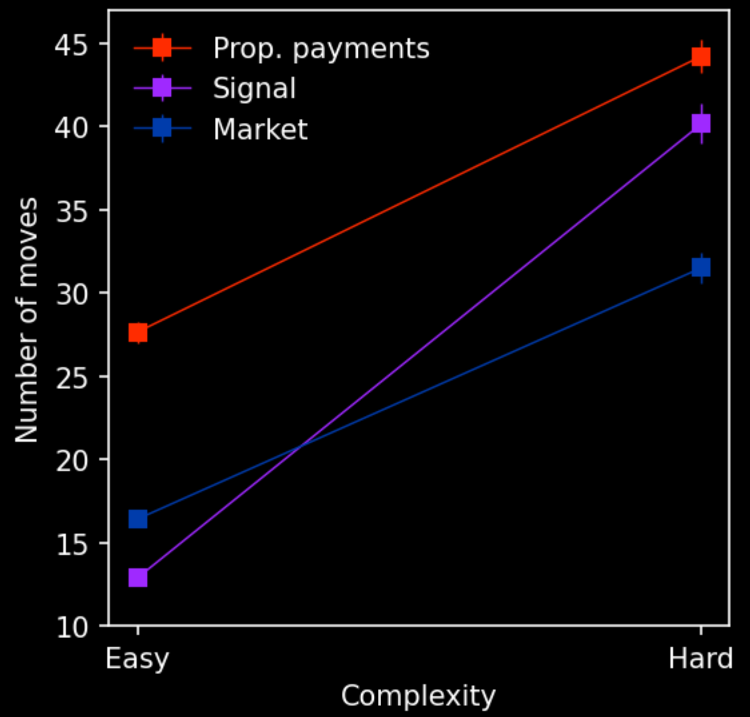
1. **Quality**
   Probability optimal solution attained
2. **Effort**
   Number of ‘item moves’
3. **Productivity**
   Submitted value / number of moves

Quality



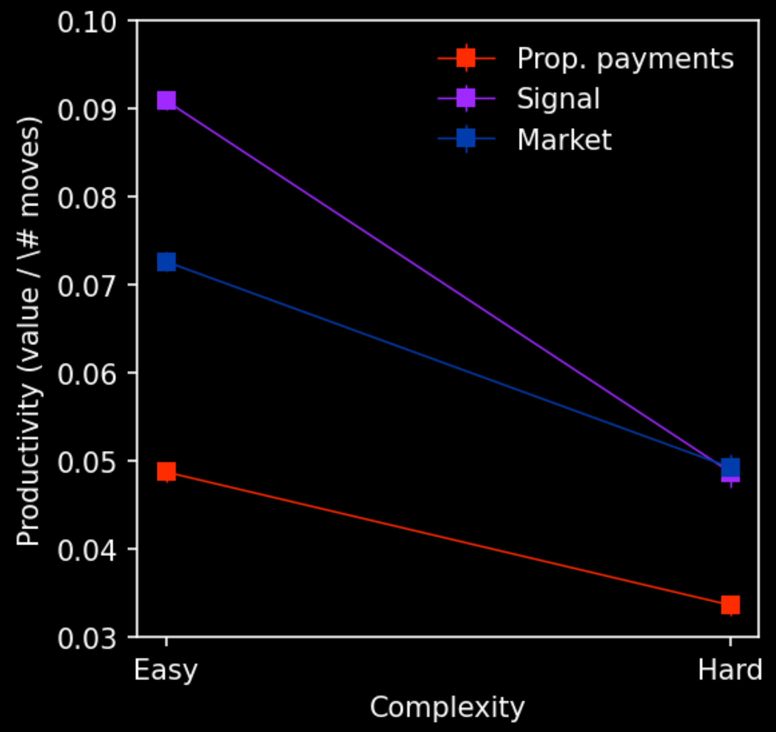
Signals help, but indirect incentives
weaken solution quality

Effort



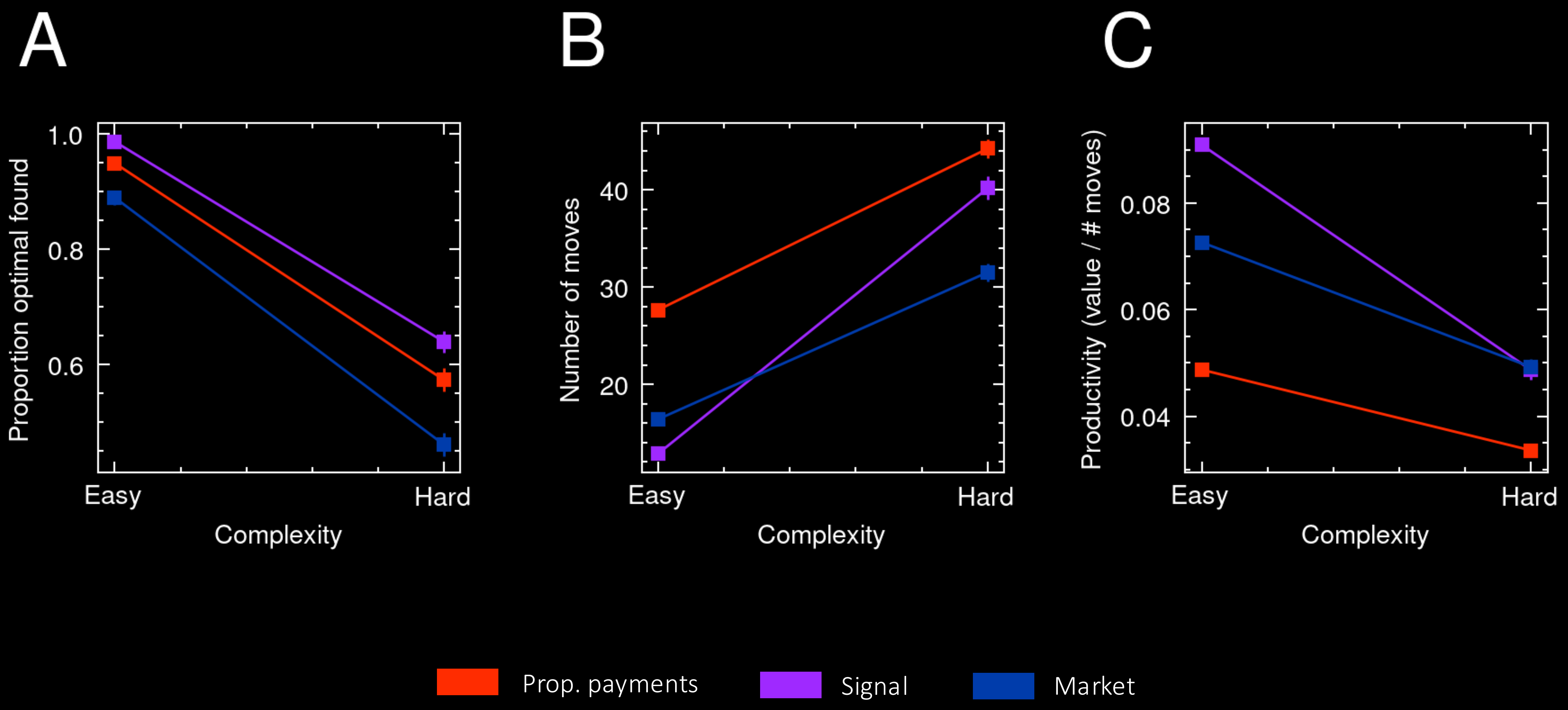
Markets and signals **reduce redundant effort**.

Productivity



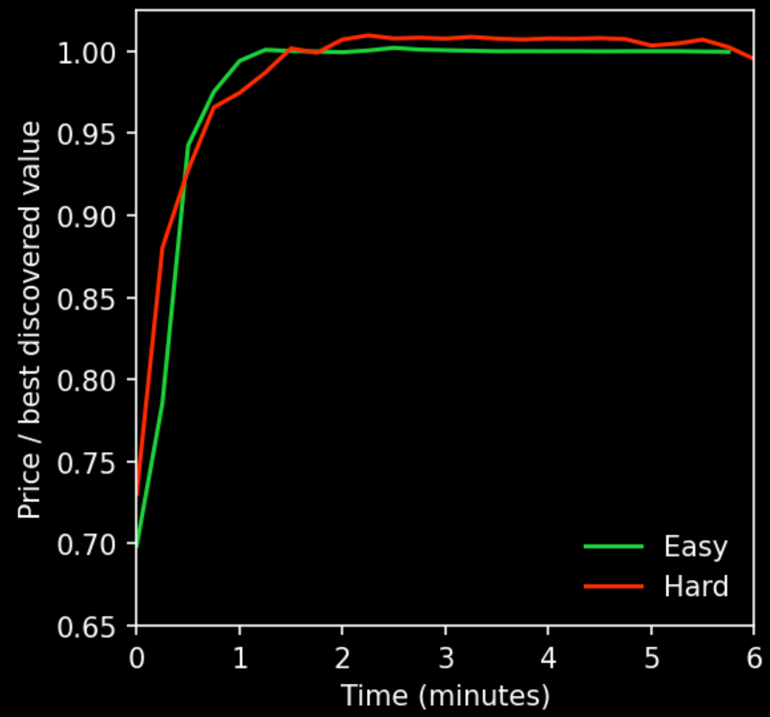
Markets and signals **increase productivity** by coordinating stop signals.

What did we learn?



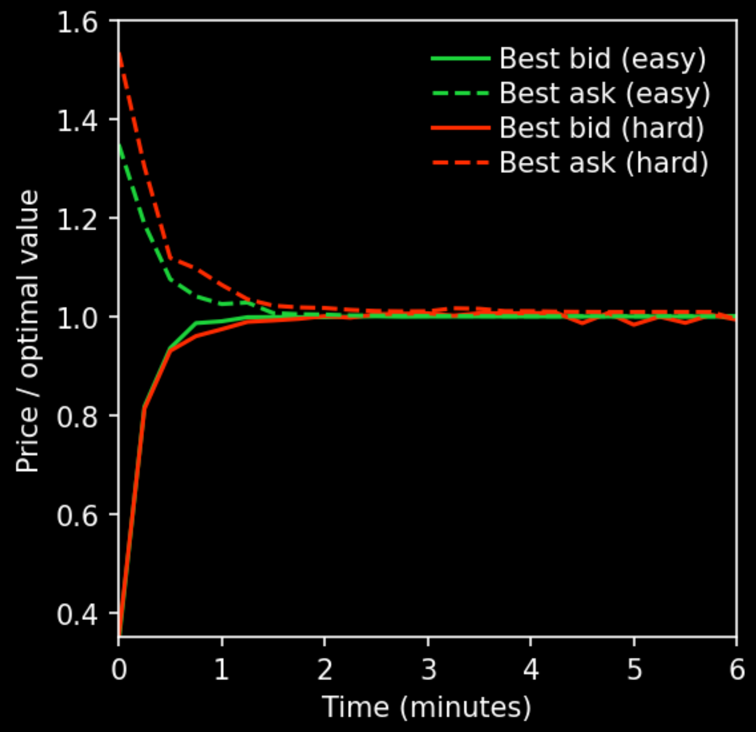
How well do prices aggregate knowledge?

Trade price



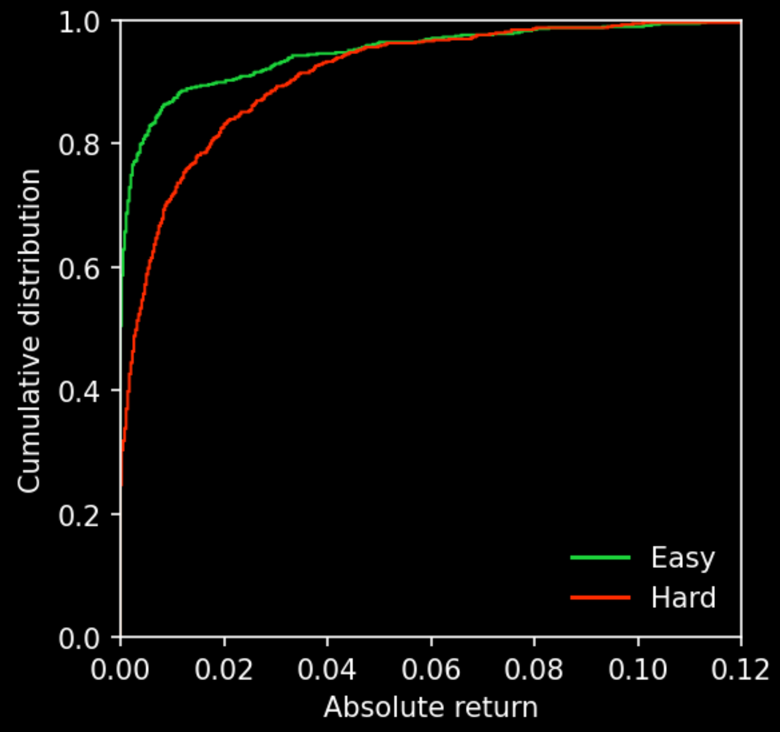
Trade prices reveal the optimum

Bid-ask spread



Bid-ask spreads signal complexity almost immediately

Returns



Complexity increases redistribution of wealth

Complexity matters
→ Difficulty reduce performance but markets and signals can mitigate this.

Markets enable coordination
→ Groups explore larger portions of the solution space, trading shares information and reduces redundant effort.

Market efficiency degrades with complexity
→ Prices are less efficient when it is computationally difficult to estimate fundamental value

Future directions
→ Investigating market failures (bubbles)
→ Distributed problems

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Thanks to my supervisors for this work →

Link to my website ↓

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