Using Quantum Agents to Model Simple Economies

Quantum Information and Optics Lab

Matthew Sprintson & Brian Zhou

Roadmap

Intro to ABMs

Methods

Simulation

Results

Discussion

Agent-Based Modeling

Agent-Based Models

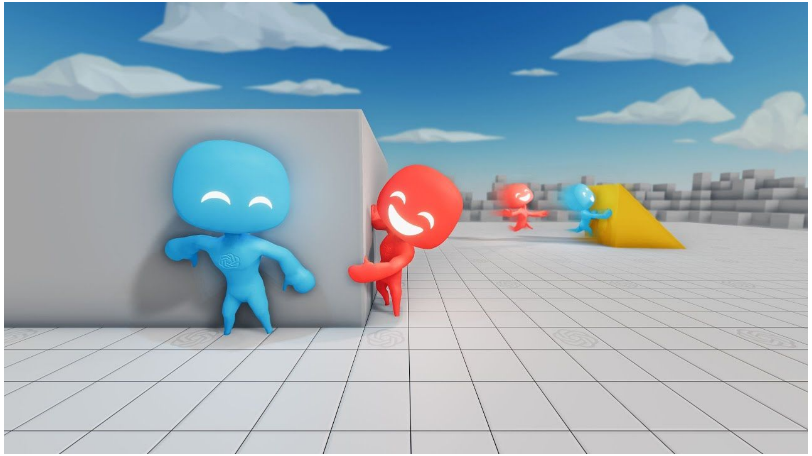
- Computer simulations
- Study how individual agents interact with each other or the environment
- Models experiments that are impractical to test in the world

Agents

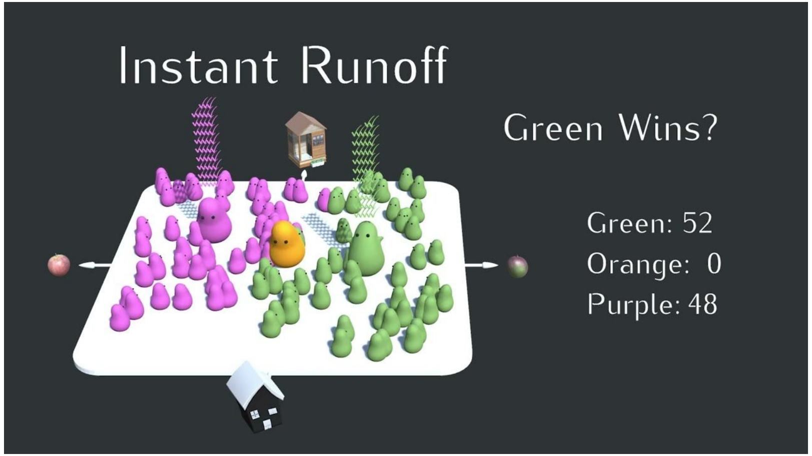
- Little "bots" that make decisions
- Behave using own logic and rules
    - Internal logic network
    - Assigned certain attributes
- Useful to analyze structures and optimization

Common applications of ABMs include epidemiology (pandemic spread), social science (grand strategy), or autonomous systems (self-driving cars)

Applications of Agent-Based Modeling

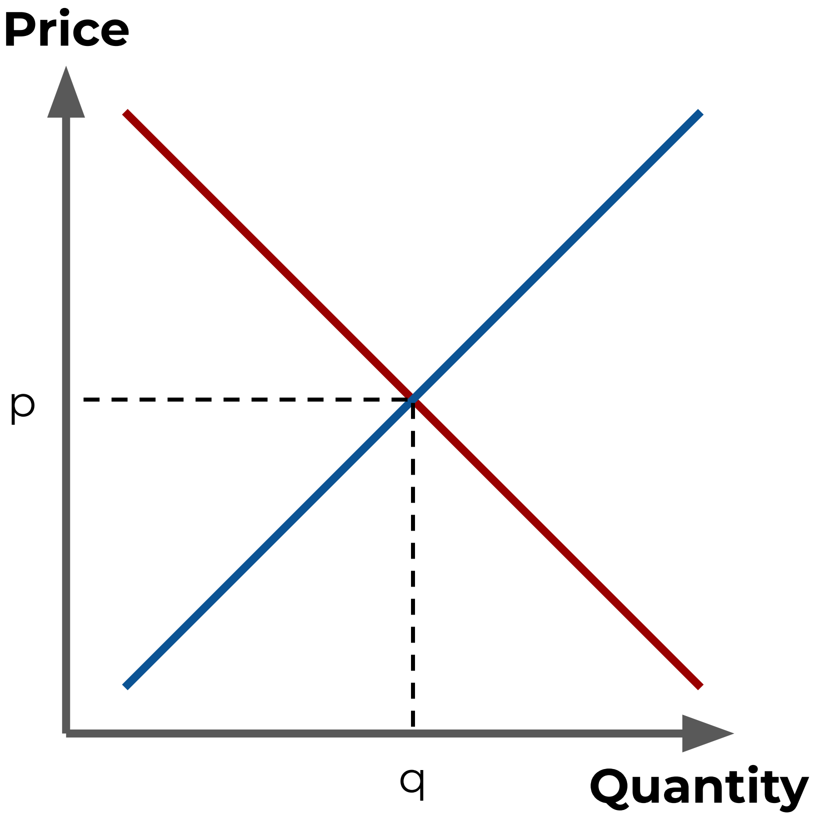


Multi-Agent Hide and Seek
OpenAI 2020



Simulating alternate voting systems
Primer 2020

Applications of Agent-Based Modeling



We'll use Agent-Based Modeling to simulate a **simple economy:**

Comprised of **buyers** and **sellers**

Only **one good** is being sold

Agents are **rational** and have a **complete memory** of transactions

Perfect communication & no loss

Questions

1. Can agents with internal Quantum circuitry reproduce empirical results given by observable economic phenomena?

2. How do Quantum agents compare with computational and Bayesian agent models?

3. How do the assumptions of the Quantum model presented in our methods compare with other agent models?

Methods

Buyer Anatomy

Memory
and
Model

Instantiated Parameters

- v_0 : The Buyer's Internal Value of the sold good on Day 0
- B_o : The Buyer's budget on Day 0
- C_0 : The Buyer's Consumer Surplus Heuristic
- μ_0 : The Buyer's diminishing marginal utility of the good

Exchange Parameters

- P_m : The price that a given seller m offers
- S_m : The quantity of inventory that a given seller m has

Memory and Model

- The Buyer's memory includes every transaction ever made in the market, stored as the parameters below with an "output" of 1 or 0, depending on whether the Buyer purchased an item or not.
- The Model will input all 4 instantiated parameters and 2 exchange parameters and output a "1" or a "0" based on a Naïve Bayes function.

Instantiated Parameters

- The internal value of the good v_0 will be stochastically instantiated at the beginning of the cycle within a certain bound.
- The Budget B_o is stochastically instantiated and replenished at the beginning of each day cycle.
- A measure of the Buyer's diminishing marginal utility of the good is μ_0. As the buyer continues to purchase goods, μ_0 will increase exponentially, such that $\mu_n = f(n)$ and the amount the buyer is willing to pay is $v_0 - \mu_n$ for the n-th item the buyer purchases.
- The Consumer Surplus Heuristic, C_0, the net amount that the buyer was willing to pay minus the amount the buyer paid.

Seller Anatomy

Memory and Model

- The seller's memory includes all parameters and their respective prices for every seller in the market.
- The model takes in all parameters, excluding price, and uses a Naïve Bayesian estimator to predict the most likely price movement for the next round. The price movement, "1" or "-1," is multiplied by λ and added to the current price to determine the price for the next round. The model also takes in another parameter, a "-1" or "1" depending on whether or not the seller's profit increased or decreased from the last round.

Instantiated Parameters

- The Price P_j is determined by the Naïve Bayes function after the second round through an evaluation of the other instantiated parameters.
- The Inventory I_j is dependent on a linear equation with Price as an input.
- The cost of production X_j in the short-run is constant for each unit produced.
- The revenue R_j is calculated by multiplying the Price by the amount sold, and the profit Pr_j is calculated by then subtracting the net cost of production.

Memory and Model

Instantiated Parameters

- P_j : The seller's price in round j.
- I_j : The seller's inventory in round j
- X_j : The seller's cost of production for round j
- R_j : The seller's revenue in round j
- Pr_j : The seller's profit in round j
- λ : A factor which modulates price movement

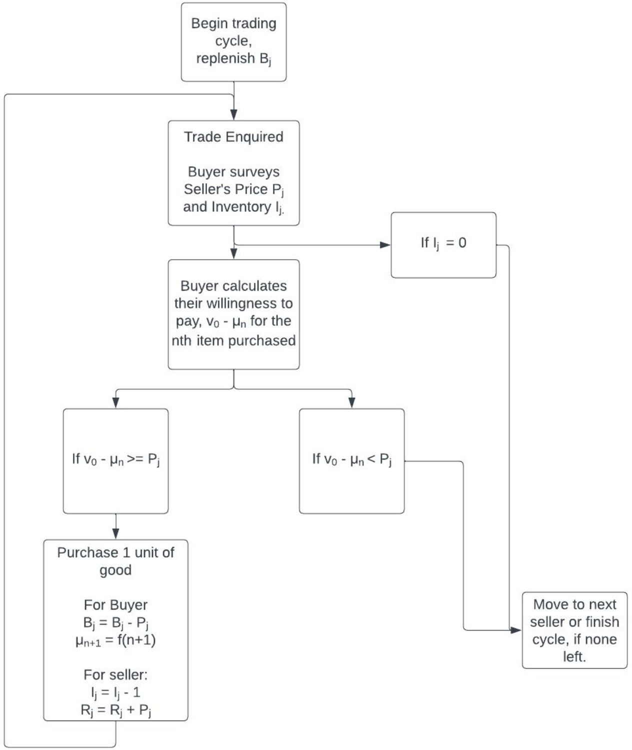
The Market

Buyers

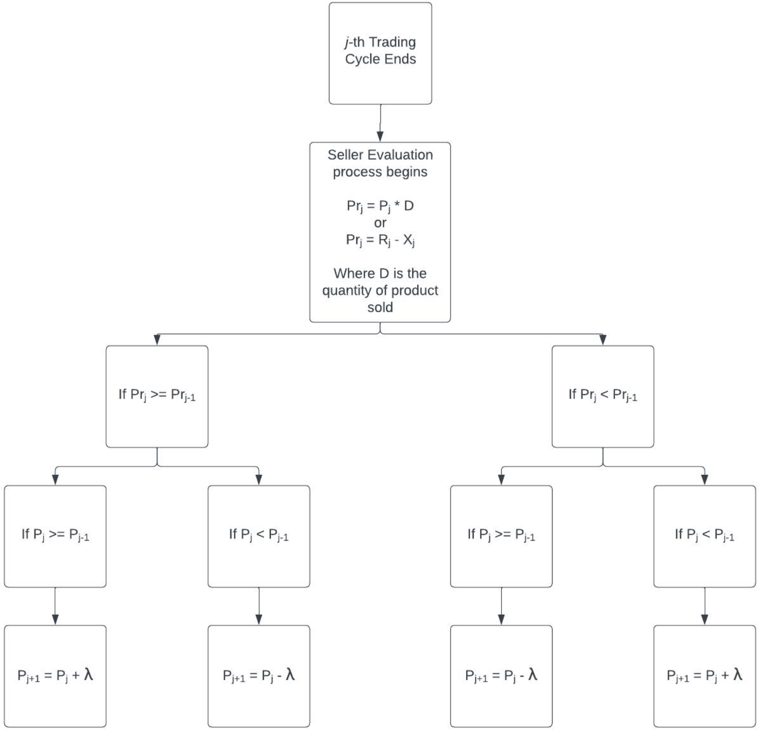
Sellers

1. The Pre-cycle Stage
   - Resents Budget and Inventory
   - Calculates Parameters
2. The Cycle Stage
   - Buyers initiate trade with sellers
   - Parameters adjusted to account
   - Good circulate
3. The Post-cycle Stage
   - All data recorded in memory
   - Price evaluation via logic circuit

Computational, Bayesian, and Quantum Agents



Buyer



Seller

Computational, Bayesian, and Quantum Agents

Bayesian agents train off previous market data and current market data.

- They hold current price indicators and other market parameters in lower regard.

$$P_{j+1} = P_j + \lambda \cdot f(I_j, X_j, R_j, Pr_j, Pr_j - Pr_{j-1})$$

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

- Bonus Friend! Mixed Agent:

```
def postSaleUpdate(self):
    pointer = random.choice([0,1])
    if pointer == 1 and self.turn >2:
        self.postSaleUpdateBayes()
    else:
        self.postSaleUpdateComp()
```

Computational, Bayesian, and Quantum Agents

Dunjko et al. 2015: agents using quantum environments

Sriarunothai et al. 2019: ion-trap processors speed up decision making

Saggio et al. 2021: hybrid reinforcement learning reduces learning time

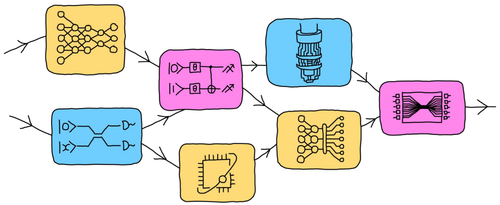
Sarkar et al. 2021: QPT algorithms create better cost function optimization

Elliott et al. 2022: quantum long-term adaptive learning improves the agent's memory recall

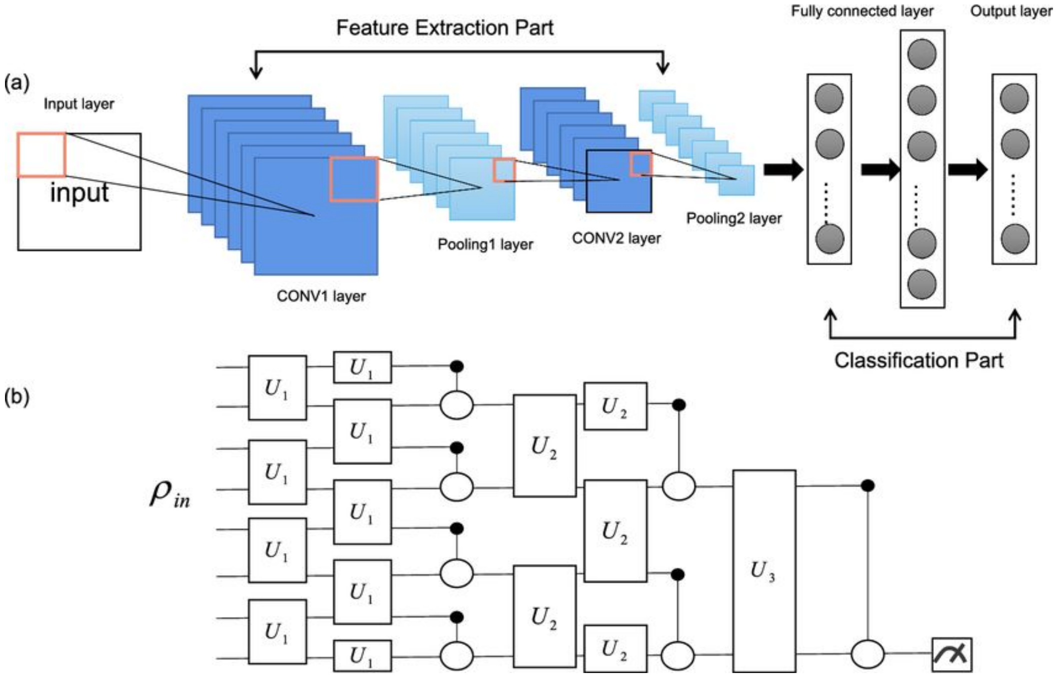
Yun et al. 2023: few-shot training of QNNs creates faster convergence with higher reward utilities

Computational, Bayesian, and Quantum Agents

Quantum systems improve an agent's **runtime**, **utility function**, and **convergence speed**



PENNYLANE

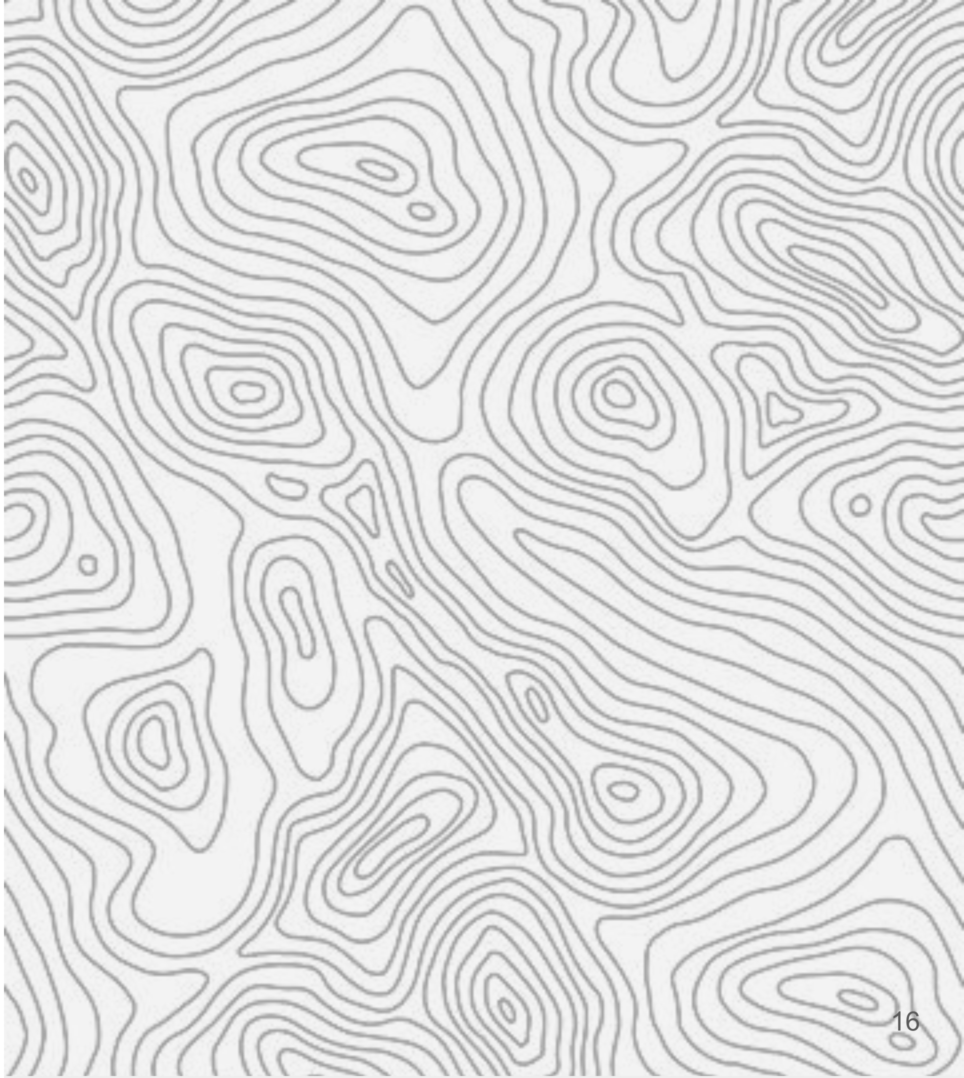


CNN and QCNN Structures
Gong et al. 2024

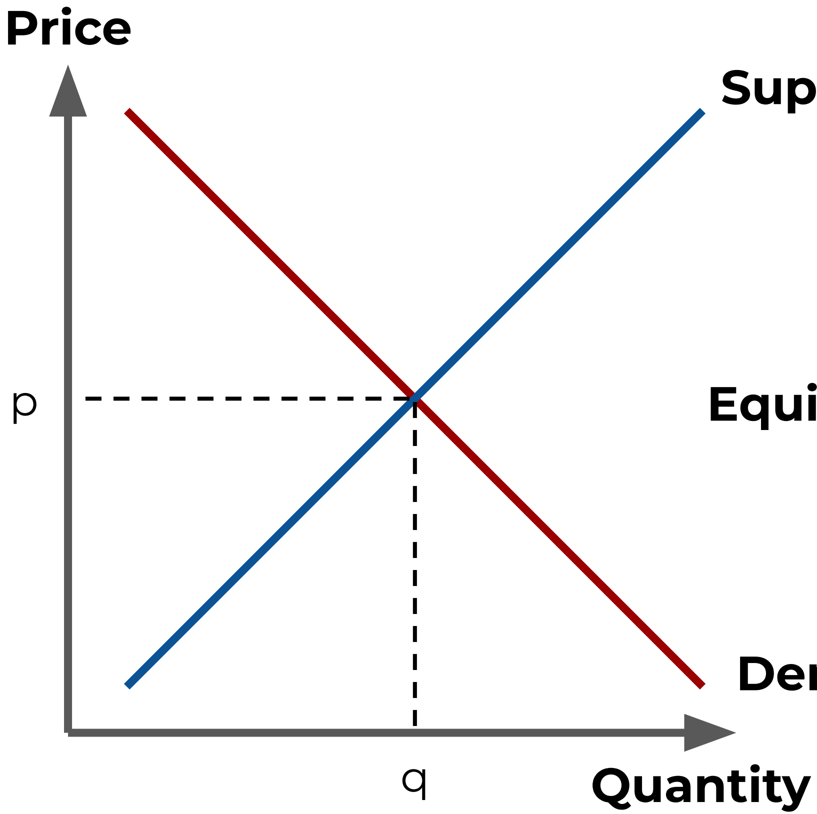
Results

Question 1:

Can agents with internal Quantum circuitry reproduce empirical results given by observable economic phenomena?



Computational, Bayesian, and Quantum Agents



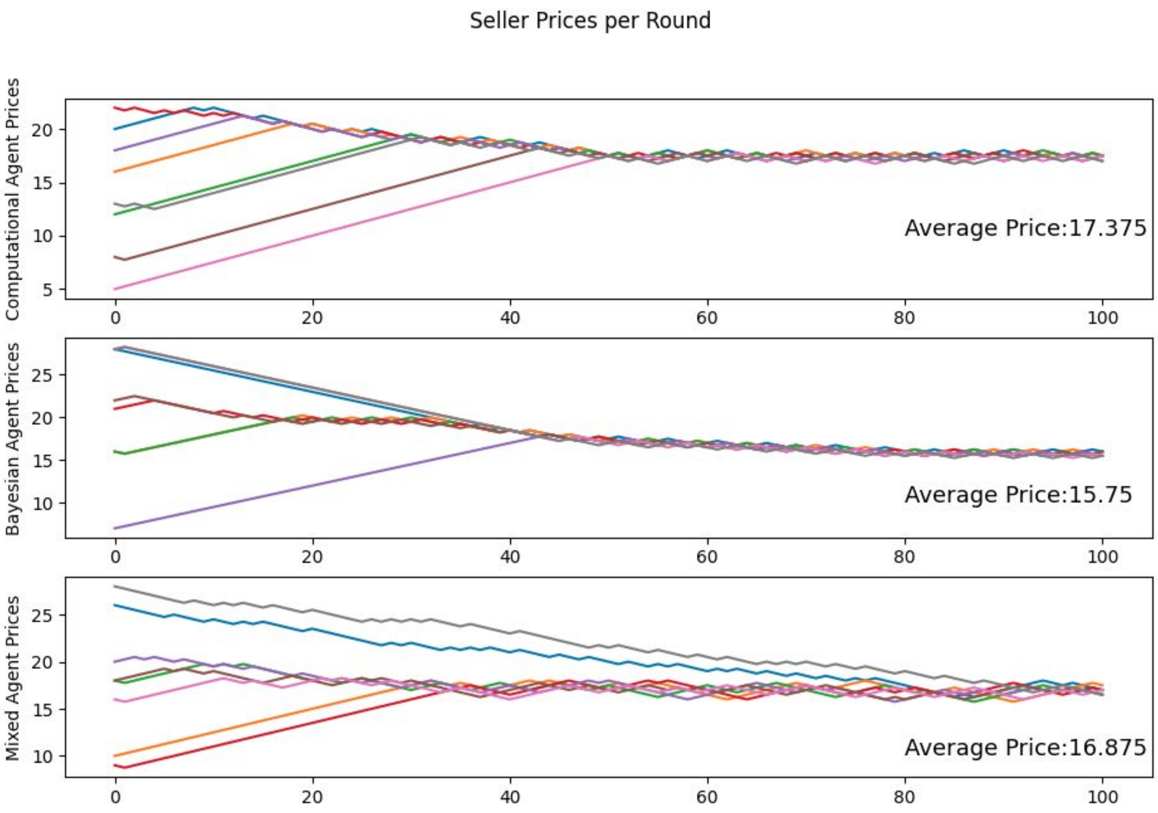
Supply = $(x-1)$

Equilibrium Price = $17.8

Demand = $15\left(\frac{300-15x}{15}\right)$

Computational, Bayesian, and Quantum Agents

Equilibrium Price = $17.8

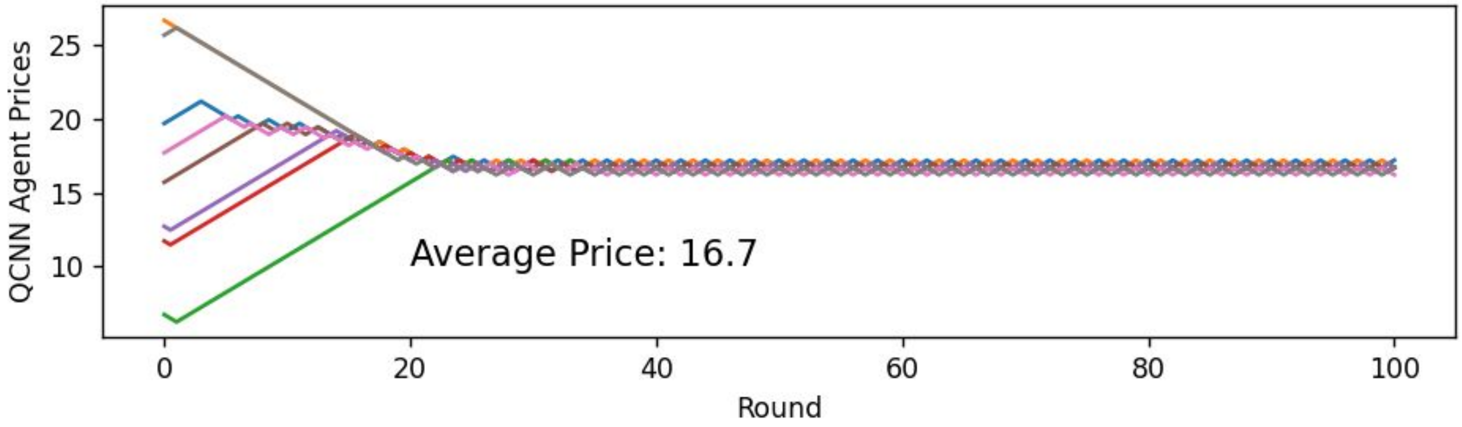


Takeaways About relationship between Market, Rationality, and Behavior

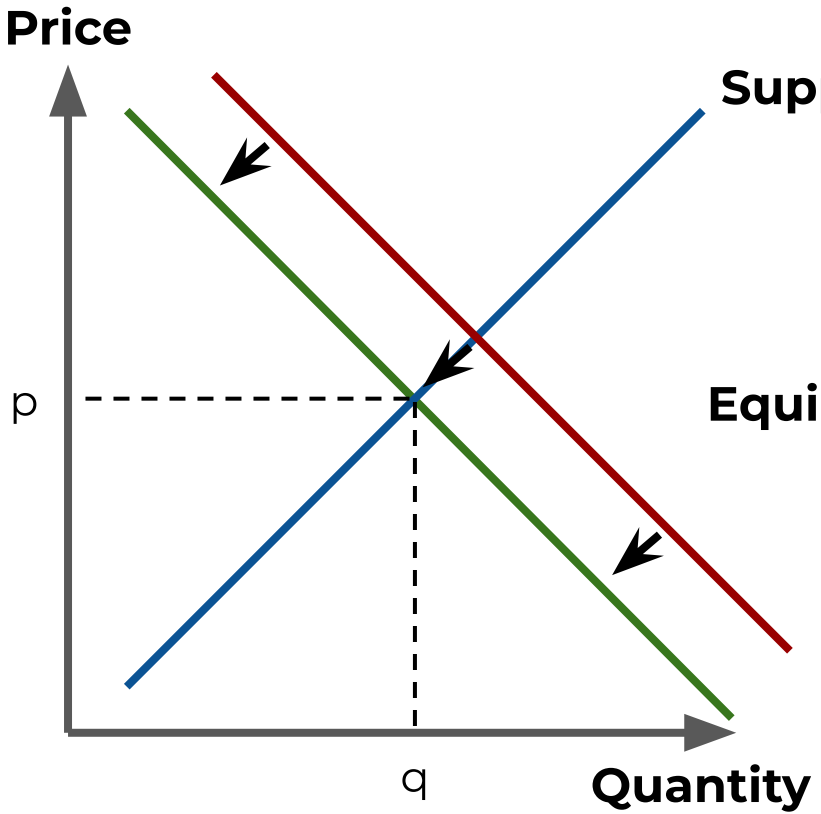
Computational, Bayesian, and Quantum Agents

Equilibrium Price = $17.8

Takeaways about the relationship between Market, Rationality, and Behavior



Computational, Bayesian, and Quantum Agents



Supply = $(x-1)$

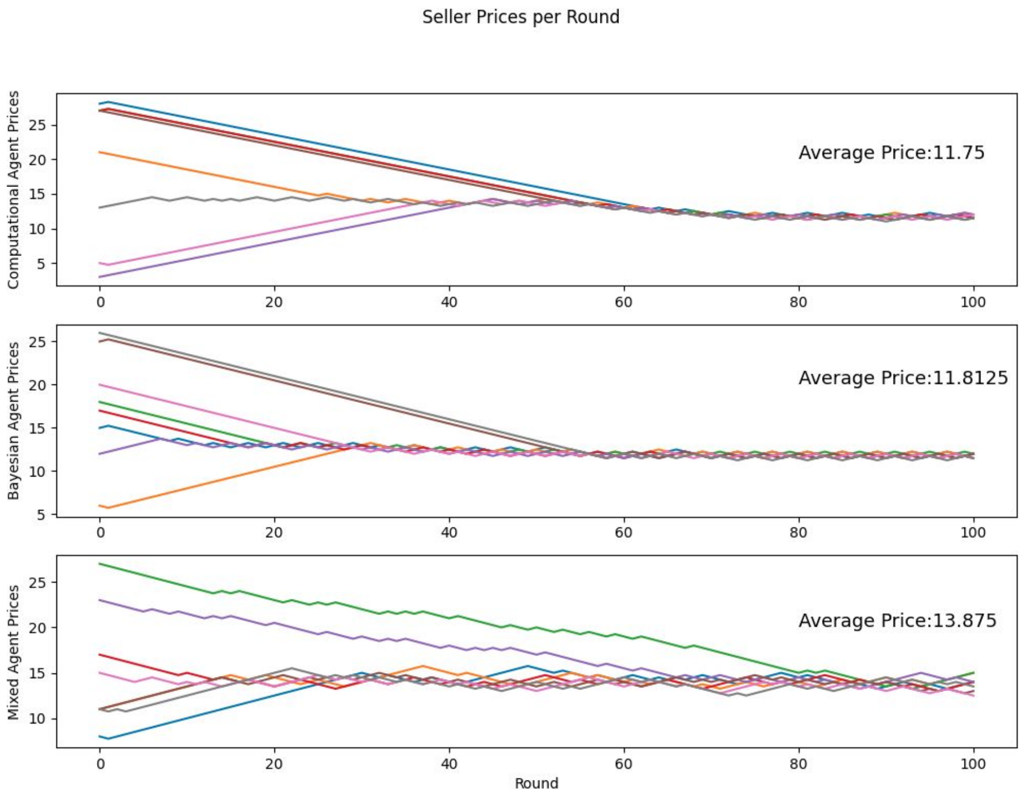
Equilibrium Price = $11.3

Demand$_1$ = $15\left(\frac{300-15x}{15}\right)$

Demand$_2$ = $11\left(\frac{200-15x}{15}\right)$

Computational, Bayesian, and Quantum Agents

Equilibrium Price = $11.3



Average Price decreases!

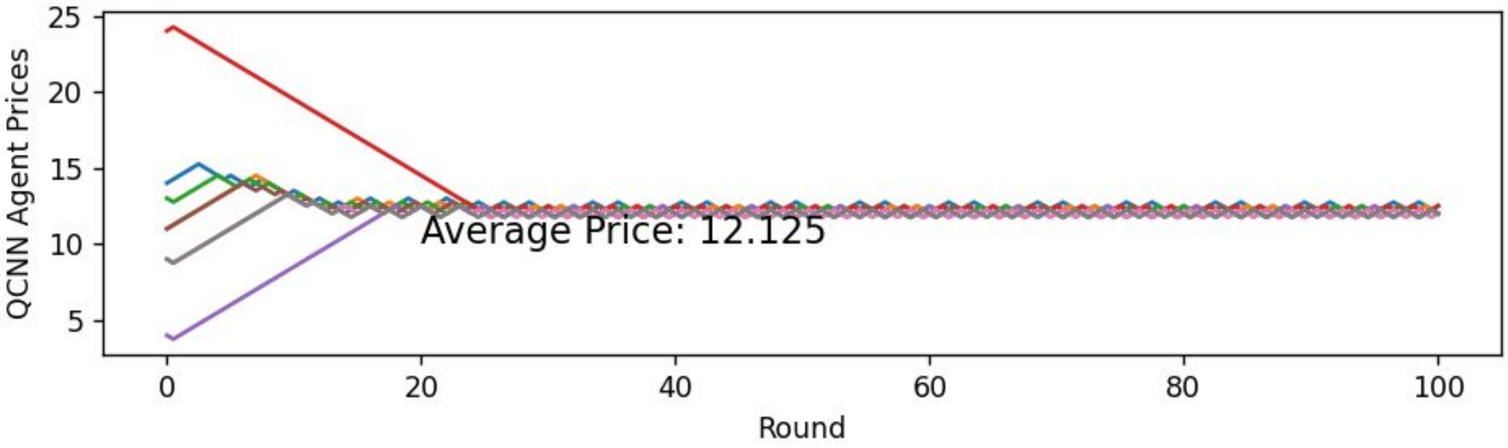
Agents are following market trends

Computational, Bayesian, and Quantum Agents

Equilibrium Price = $11.3

Average Price decreases!

Agents are following market trends

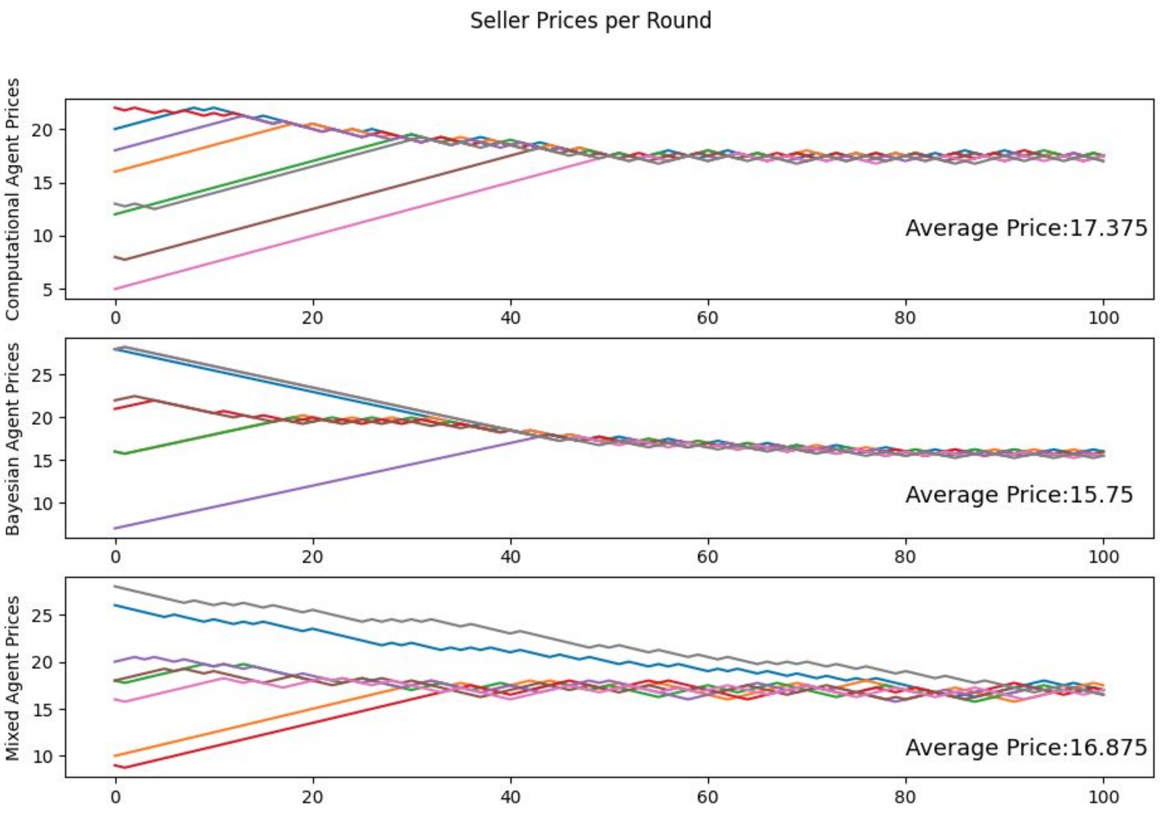


Question 2:

How do Quantum agents compare with computational and Bayesian agent models?

Computational, Bayesian, and Quantum Agents

Equilibrium Price = $17.8



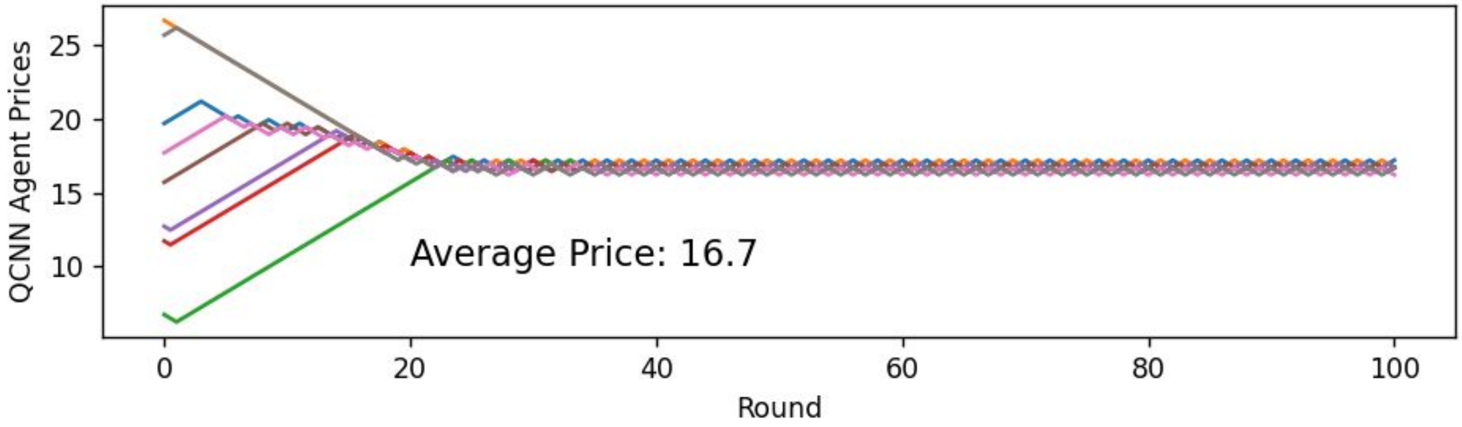
Takeaways About relationship between Market, Rationality, and Behavior

Computational, Bayesian, and Quantum Agents

Equilibrium Price = $17.8

Improved equilibrium from Bayes

Faster convergence to equilibrium; **23 rounds** vs. 51, 43, 34



Question 3:

How do the assumptions of the Quantum model presented in our methods compare with other agent models?

Acknowledgements

Thank you to Mr. Hannum for his continued support and guidance of our project

Questions?