

Algorithmic Collusion in Vertical Supply Chains: A Multi-Agent Reinforcement Learning Framework

Authors:

Yash Tyagi, Herbert Dawid

Algorithmic-collusion literature typically considers horizontally competing firms that set consumer prices directly. We study algorithmic collusion in a vertical supply chain where autonomous agents interact across upstream and downstream market layers. Manufacturers learn wholesale-pricing strategies, while retail firms learn final prices for differentiated consumer products. Wholesale prices also affect sourcing decisions, linking upstream competition, downstream pricing, and the allocation of demand across suppliers.

The model accommodates asymmetric supply relationships, multiproduct firms, and different degrees of vertical integration. Agents independently adapt their strategies through repeated Q-learning. Learned outcomes are compared with configuration-specific static Nash and vertical-chain monopoly benchmarks, while deviation experiments examine whether supracompetitive coordination can be sustained through strategic responses within or across market layers.

The computational burden grows rapidly with the number of firms and products and, crucially, with the number of grid points used for each price instrument. The joint state and action spaces expand combinatorially across these price grids. This creates a severe curse of dimensionality for tabular Q-learning, the standard approach in much of the economics literature on algorithmic collusion. Deep Q-networks mitigate this limitation through function approximation, making it possible to study larger and more structurally complex configurations. The general model can therefore be scaled along the number of agents, products, supply links, and pricing choices. As the resulting computational demands increase, HPC resources offer a potential means of exploring even broader configuration and parameter spaces through more extensive simulation experiments.