Chapter LII
Co-Evolving Better Strategies in Oligopolistic Price Wars

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ABSTRACT

Using empirical market data from brand rivalry in a retail ground-coffee market, we model each idiosyncratic brand's pricing behavior using the restriction that marketing strategies depend only on profit-relevant state variables, and use the genetic algorithm to search for co-evolved equilibria, where each profit-maximizing brand manager is a stimulus-response automaton, responding to past prices in the asymmetric oligopolistic market. This chapter is part of a growing study of repeated interactions and oligopolistic behavior using the GA.

INTRODUCTION

We use simulated evolution to explore oligopolistic behavior in a (retail) market with up to four strategic sellers, comparing our simulation results with historical data derived from a retail market for ground, vacuum-sealed coffee beans. We find that our boundedly rational sellers perform well (as measured by their average weekly profits) compared to their historical counterparts, despite their limited memory and constrained marketing actions.

Significant features of our work are: first, our agents are heterogeneous: they respond idiosyncratically to others' actions, they have distinct costs, face distinct demand curves, and so earn distinct profits. For this reason, we cannot ignore the identities of the separate players, which would be convenient, were the players identical. Second, we use the genetic

Table 1. The nine brands: Average price and market share

Brand	Price	Market Share
Folgers	$2.33	21%
Maxwell House	$2.22	20%
Chock Full O' Nuts	$2.02	11%
Maxwell House Master Blend	$2.72	10%
Chase & Sanbourne	$2.34	4%
Hills Bros.	$2.13	4%
Yuban	$3.11	1%
All Other Branded	$1.96	3%
All Other Private Labels	$1.95	27%

algorithm (GA) to model the players' learning. To avoid "social learning" (Vriend 2000), when players drawn from a single population pass information to their "offspring" through the genotype (an extra-market mechanism), we use distinct populations for the four strategic sellers, which precludes extra-market communication and learning. Third, we use stochastic sampling (commonly know as Monte Carlo sampling; see Judd, 1998) to generate a distribution of marketing behaviors across the sellers: given the stochastic nature of the GA, and the complexity of the genotypes and phenotypes, we use distinct random seeds to generate 50 distinct outcomes.

Computer scientists have developed machine learning, such as the GA (Holland, 1976, 1992; Mitchell, 1996; Goldberg, 1989) and classifier systems (Holland, 1976, 1992) as means of optimizing—of finding the argmax of functions not amenable to calculus-based methods of solution. Social scientists have used and developed these tools (Marks, 1989, 2002; Arifovic, 1993), but less as optimizers and more as generators of "adaptive plans" or "structures that perform well" in complex systems (Holland, 1975, 1992), by modeling adaptive economic agents (Holland & Miller, 1992) that interact. This chapter demonstrates use of the GA in this spirit.

Table 2. Asymmetries of the four strategic brands

	Own-Price Elasticity of Market Share	*AVC* ($/lb.)
Folgers	–4.4	$1.39
Maxwell House	–3.9	$1.32
Chock Full O' Nuts	–4.7	$1.19
Hills Bros.	–0.5	$1.18

OLIGOPOLY THEORY

Rivalry among retail brand managers in a market for vacuum-sealed ground coffee beans can be seen to possess characteristics that clearly reflect the oligopolistic nature of the repeated interaction: the brands are seen as imperfect substitutes by the buyers; the sales of any one brand, if stimulated by heightened marketing actions, will negatively impact on the sales of other brands, and there is no single going market price for coffee. We model Bertrand asymmetric competition among firms, competing with price (and other marketing actions) rather than quantity.

We have access to 78 weeks of supermarket-scanner market data for a city in the U.S. Midwest by supermarket chain. The marketing actions (price, coupons, aisle display, advertising) remain unchanged for seven days, from midnight Saturday for all brands—a property that lends itself to simulation modeling on a digital computer.

One of us (Cooper) has developed a market model, Casper, which calculates, given all of the nine brands' marketing actions, the volume of sales of each brand, the brands' revenues, and profits (Cooper & Nakanishi, 1988).[1] The brands differ not only in the demand response of the market (each of their price elasticities of demand is distinct), but also in their costs. The brands are truly hereogeneous, as seen in Tables 1 and 2.

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