9. Dynamic Games: Applications

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9.1 Environmental Regulation in the Cement Industry

Ryan studies the effects in the US cement industry of the 1990 Amendments to Air Clean Act. Ryan's model presents a dynamic game of oligopoly competition where firms compete in quantities but they also make investment decisions in capacity and in market entry/exit, and they are heterogeneous in their different costs, that is,marginal costs, fixed costs, capacity investment costs, and sunk entry costs.

Below, we examine the following points of the paper. (a) Motivation and Empirical Questions; (b) The US Cement Industry; (c) The Regulation (Policy Change); (d) Empirical Strategy; (e) Data; (f) Model; (g) Estimation and Results.

9.1.1 Motivation and Empirical Questions

Most previous studies that measure the welfare effects of environmental regulation (ER) have ignored dynamic effects of these policies.

ER has potentially important effects on firms' entry and investment decisions, and, in turn, these can have important welfare effects.

This paper estimates a dynamic game of entry/exit and investment in the US Portland cement industry.

The estimated model is used to evaluate the welfare effects of the 1990 Amendments to the Clean Air Act (CAA).

9.1.2 The US Cement Industry

For the purpose of this paper, the most important features of the US cement industry are: (1) Indivisibilities in capacity investment, and economies of scale; (2) Highly polluting and energy intensive industry; and (3) Local competition, and highly concentrated local markets

Indivisibilities in capacity investment, and economies of scale. Portland cement is the binding material in concrete, which is a primary construction material. It is produced by first pulverizing limestone and then heating it at very high temperatures in a rotating kiln furnace. These kilns are the main piece of equipment. Plants can have one or more kilns (indivisibilities). Marginal cost increases rapidly when a kiln is close to full capacity.

Highly polluting and energy intensive industry. The industry generates a large amount of pollutants by-products. High energy requirements and pollution make the cement industry an important target of environmental policies.

Local competition, and highly concentrated local markets. Cement is a commodity difficult to store and transport, as it gradually absorbs water out of the air rendering it useless. This is the main reason why the industry is spatially segregated into regional markets. These regional markets are very concentrated.

9.1.3 The Regulation (Policy Change)

In 1990, the Amendments to the Clean Air Act (CAA) added new categories of regulated emissions. Also, cement plants were required to undergo an environmental certification process. It has been the most important new environmental regulation affecting this industry in the last three decades. This regulation may have increased sunk costs, fixed operating costs or even investment costs in this industry.

9.1.4 Empirical Strategy

Previous evaluations of these policies have ignored effects on entry/exit and on firms' investment. They have found that the regulation contributed to reduce marginal costs and therefore prices. Positive effects on consumer welfare and total welfare. Ignoring effects on entry/exit and on firms' investment could imply an overestimate of these positive effects.

Ryan specifies a model of the cement industry, where oligopolists make optimal decisions over entry, exit, production, and investment given the strategies of their competitors. He estimates the model for the cement industry using a 20 year panel and allowing the structural parameters to differ before and after the 1990 regulation. Changes in cost parameters are attributed to the new regulation. The MPEs before and after the regulation are computed and they are used for welfare comparisons.

Comments on this empirical approach and its potential limitations: (a) anticipation of the policy; (b) technological change; (c) learning about the new policy.

9.1.5 Data

Period: 1980 to 1999 (20 years); 27 regional markets. Index local markets by m, plants by i and years by t.

$$Data = \{S_{mt},\ W_{mt},\ P_{mt},\ n_{mt},\ q_{imt},\ i_{imt},\ s_{imt}\}$$

S_{mt} = Market size; W_{mt} = Input prices (electricity prices, coal prices, natural gas prices, and manufacturing wages); P_{mt} = Output price; n_{mt} = Number of cement plants; q_{imt} = Quantity produced by plant i; s_{imt} = Capacity of plant i (number and capacity of kilns); i_{imt} = Investment in capacity by plant i.

9.1.6 Model

Regional homogenous-goods market. Firms compete in quantities in a static equilibrium, but they are subject to capacity constraints. Capacity is the most important strategic variable. Firms invest in future capacity and this decision is partly irreversible (and therefore dynamic). Incumbent firms also make optimal decisions over whether to exit.

Inverse demand curve (iso-elastic):

$$\log P_{mt} = \alpha_{mt} + \frac{1}{\varepsilon} \log Q_{mt}$$

Production costs:

$$\begin{aligned} C(q_{imt}) &= (MCOST + \omega_{imt})\, q_{imt} \\ &\quad + CAPCOST * I\left\{\frac{q_{imt}}{s_{imt}} > BINDING\right\}\left(\frac{q_{imt}}{s_{imt}} - BINDING\right)^2 \end{aligned}$$

s_{imt} = installed capacity; q_{imt}/s_{imt} = degree of capacity utilization; ω_{imt} = private information shock; $MCOST$, $CAPCOST$ and $BINDING$ are parameters.

Investment costs

$$\begin{aligned} IC_{imt} &= I\{i_{imt} > 0\}\left(ADJPOS + INVMCPOS * i_{imt} + INVMCPOS2 * i_{imt}^2\right) \\ &\quad + I\{i_{imt} < 0\}\left(ADJNEG + INVMCNEG * i_{imt} + INVMCNEG2 * i_{imt}^2\right) \end{aligned}$$

Entry costs

$$EC_{imt} = I\{s_{imt} = 0 \text{ and } i_{imt} > 0\} \left(SUNK + \varepsilon_{imt}^{EC}\right)$$

In equilibrium, investment is a function:

$$i_{imt} = i(\alpha_{mt}, W_{mt}, s_{imt}, s_{-imt})$$

Similarly, entry and exit probabilities depend on $(\alpha_{mt}, W_{mt}, s_{imt}, s_{-imt}, \varepsilon_{imt}^{EC})$.

9.1.7 Estimation and Results

Estimation of demand curve. Includes local market region fixed effects (estimated with 19 observations per market). Instruments: local variation in input prices. The market specific demand shocks, A_{mt}, are estimated as residuals in this equation.

Estimation of variable production costs. From the Cournot equilibrium conditions. Firm specific cost shocks, ω_{imt}, are estimated as residuals in this equation.

Estimation of investment functions. Assumption:

$$i_{imt} = i(\alpha_{mt}, W_{mt}, s_{imt}, s_{-imt}) = i\left(\alpha_{mt}, W_{mt}, s_{imt}, \sum_{j \neq i} s_{jmt}\right)$$

9.2 Dynamic game of store location

Opening (or closing) a store is a forward-looking decision with significant non-recoverable entry costs, mainly owing to capital investments which are both firm and location-specific. The sunk cost of setting up new stores, and the dynamic strategic behavior associated with them, are potentially important forces behind the configuration of the spatial market structure that we observe in retail markets. We now present an extension of the previous model that incorporates these dynamic considerations.

Time is discrete and indexed by $t \in \{\ldots, 0, 1, 2, \ldots\}$. At the beginning of period t a firm's network of stores is represented by the vector $a_{it} \equiv \{a_{i\ell t} : \ell = 1, 2, \ldots, L\}$, where $a_{i\ell t}$ is the number of stores that firm i operates in location ℓ at period t. For simplicity, we maintain the assumption that a firm can have at most one store in a location, such that $a_{i\ell t} \in \{0, 1\}$. The market structure at period t is represented by the vector $a_t \equiv \{a_{it} : i = 1, 2, \ldots, N\}$ capturing the store network of all firms. Following the structure in the influential work on dynamic games of oligopoly competition by Ericson and Pakes (1995) and Pakes and McGuire (1994), at every period t the model has two stages, similar to the ones described in the static game above. In the second stage, taking the vector of firms' store networks a_t as given, retail chains compete in prices in exactly the same way as in the Bertrand model described in section 2.1.2. The equilibrium in this Bertrand game determines the indirect variable profit function, $VP_i^*(a_t; z_t)$, where z_t is a vector of exogenous state variables in demand and costs. Some components of z_t may be random variables, and their future values may not be known at the current period. In the first stage, every firm decides its network of stores in the next period, $a_{i,t+1}$, and pays at period t the entry and exit costs associated to opening and closing stores. The period profit of a firm is $\pi_i(a_{i,t+1}, a_t, z_t) = VP_i^*(a_t; z_t) - FC(a_{it}; z_t) - AC_i(a_{i,t+1}, a_{it})$, where FC_i is the fixed cost of operating the network, and AC_i is the cost of adjusting the network from a_{it} to $a_{i,t+1}$, that is, costs of opening and closing stores. A firm chooses its new network $a_{i,t+1}$ to maximize the sum of its discounted expected future profits.

A Markov perfect equilibrium of this dynamic game is an N-tuple of strategy functions $\{\alpha_i^*(a_t, z_t) : i = 1, 2, \ldots, N\}$ such that every firm maximizes its expected intertemporal profit:

$$\alpha_i^*(a_t, z_t) = \arg\max_{a_{i,t+1}} \left[\pi_i(a_{i,t+1}, a_t, z_t) + \delta\, \mathbb{E}_t(V_i^{\alpha^*}(a_{i,t+1}, \alpha_{-i}^*(a_t, z_t), z_{t+1}) \right] \tag{9.1}$$

where $\delta \in (0,1)$ is the discount factor, and $V_i^{\alpha^*}(a_{it}, a_{-it}, z_t)$ is the value of firm i when firms' networks are equal to a_t, the value of exogenous state variables is z_t, and the other firms follow strategies α_{-i}^*.

9.2.1 Single-store firms

When the entry cost is partially sunk, firms' entry decisions depend on their incumbency status, and dynamic models become more relevant. The role of sunk entry costs in shaping market structure in an oligopoly industry was first empirically studied by Bresnahan and Reiss (1994). They estimate a two-period model using panel data on the number of dentists. Following recent developments in the econometrics of dynamic games of oligopoly competition, several studies have estimated dynamic games of market entry-exit in different retail industries.

Aguirregabiria and Mira (2007) estimate dynamic games of market entry and exit for five different retail industries: restaurants, bookstores, gas stations, shoe shops, and fish shops. They use annual data from a census of Chilean firms created for tax purposes by the Chilean Internal Revenue Service during the period 1994–99. The estimated models show significant differences in fixed costs, entry costs, and competition effects across the five industries, and these three parameters provide a precise description of the observed differences in market structure and entry-exit rates between the five industries. Fixed operating costs are a very important component of total profits of a store in the five industries, and they range between 59 percent (in restaurants) to 85 percent (in bookstores) of the variable profit of a monopolist in a median market. Sunk entry costs are also significant in the five industries, and they range between 31 percent (in shoe shops) and 58 percent (in gas stations) of a monopolist variable profit in a median market. The estimates of the parameter that measures the competition effect show that restaurants are the retailers with the smallest competition effects, which might be explained by a higher degree of horizontal product differentiation in this industry.

Suzuki (2013) examines the consequence of tight land use regulation on market structure of hotels through its impacts on entry costs and fixed costs. He estimates a dynamic game of entry-exit of mid-scale hotels in Texas that incorporates detailed measures of land use regulation into cost functions of hotels. The estimated model shows that imposing stringent regulation increases costs considerably and has substantial effects on market structure and hotel profits. Consumers also incur a substantial part of the costs of regulation in the form of higher prices.

Dunne et al. (2013) estimate a dynamic game of entry and exit in the retail industries of dentists and chiropractors in the US, and use the estimated model to evaluate the effects on market structure of subsidies for entry in small geographic markets, that is, markets that were designated by the government as Health Professional Shortage Areas (HPSA). The authors compare the effects of this subsidy with those of a counterfactual subsidy on fixed costs, and they find that subsidies on entry costs are cheaper, or more effective for the same present value of the subsidy.

Yang (2020) extends the standard dynamic game of market entry-exit in a retail market by incorporating information spillovers from incumbent firms to potential entrants. In his model, a potential entrant does not know a market-specific component in the level of profitability of a market (for example, a component of demand or operating costs). Firms learn about this profitability only when they actually enter that market. In this context, observing incumbents staying in this market is a positive signal for potential entrants about the quality of this market. Potential entrants use these signals to update their beliefs about the profitability of the market (that is, Bayesian updating). These information spillovers from incumbents may contribute to explaining why we observe retail clusters in some geographic markets. Yang estimates his model using data from the fast food restaurant industry in Canada, which goes back to the initial conditions of this industry in Canada. He finds significant evidence supporting the hypothesis that learning from incumbents induces retailers to herd into markets where others have previously done well in, and to avoid markets where others have previously failed in.

9.2.2 Multi-store firms

A structural empirical analysis of economies of density, cannibalization, or spatial entry deterrence in retail chains requires the specification and estimation of models that incorporate dynamics, multi-store firms, and spatial competition. Some recent papers present contributions on this research topic.

Holmes (2011) studies the temporal and spatial pattern of store expansion by Walmart during the period 1971–2005. He proposes and estimates a dynamic model of entry and store location by a multi-store firm similar to the one that we have described in section 2.1.3 above. The model incorporates economies of density and cannibalization between Walmart stores, though it does not model explicitly competition from other retailers or chains (for example, Kmart or Target), and therefore it abstracts from dynamic strategic considerations such as spatial entry deterrence. The model also abstracts from price variation and assumes that Walmart sets constant prices across all stores and over time. However, Holmes takes into account three different types of stores and plants in the Walmart retail network: regular stores that sell only general merchandise; supercenters, that sell both general merchandise and food; and distribution centers, which are the warehouses in the network, that have also two different types: general and food. The distinction between these types of stores and warehouses is particularly important to explain the evolution of the Walmart retail network over time and space. In the model, every year Walmart decides the number and the geographic location of new regular stores, supercenters, and general and food distribution centers. Economies of density are channeled through the benefits of stores being close to distribution centers. The structural parameters of the model are estimated using the Moment Inequalities estimation method in Pakes et al. (2015). More specifically, moment inequalities are constructed by comparing the present value of profits from Walmart's actual expansion decision with the present value from counterfactual expansion decisions, which are slight deviations from the observed ones. Holmes finds that Walmart obtains large savings in distribution costs by having a dense store network.

Igami and Yang (2016) study the trade-off between cannibalization and spatial pre-emption in the fast-food restaurant industry, for example, McDonalds, Burger King, and so on. Consider a chain store that has already opened its first store in a local market. Opening an additional store increases this chain's current and future variable profits by, first, attracting more consumers and, second, preventing its rivals' future entries (pre-emption). However, the magnitude of this increase could be marginal when the new store steals customers from its existing store (cannibalization). Whether opening a new store economically makes sense or not depends on the size of the entry cost. Igami and Yang estimate a dynamic structural model and find the quantitative importance of preemptive motives. However, they do not model explicitly spatial competition, or allow for multiple geographic locations within their broad definition of a geographic market.

Schiraldi, Smith, and Takahashi (2012) study store location and spatial competition between UK supermarket chains. They propose and estimate a dynamic game similar to the one in Aguirregabiria and Vicentini (2016) that we have described in section 2.1.3. A novel and interesting aspect of this application is that the authors incorporate the regulator's decision to approve or reject supermarkets' applications for opening a new store in a specific location. The estimation of the model exploits a very rich dataset from the U.K. supermarket industry on exact locations and dates of store openings/closings, applications for store opening, approval/rejection decisions by the regulator, as well as rich data of consumer choices and consumer locations. The estimated model is used to evaluate the welfare effects of factual and counterfactual decision rules by the regulator.

9.3 Product repositioning in differentiated product markets

(Sweeting ,2007) To Be Completed

9.4 Dynamic Game of Airlines Network Competition

9.4.1 Motivation and Empirical Questions

An airline network is a description of the city-pairs (or airport pairs) that the airline connects with non-stop flights. The first goal of this paper is to develop a **dynamic game of network competition between airlines**, a model that can be estimated using publicly available data.

The model endogenizes airlines' networks, and the dynamics of these networks. Prices and quantities for each airline-route are also endogenous in the model. It extends previous work by Hendricks, Piccione, and Tan (1995, 1999) on airline networks, and previous literature on structural models of the airline industry: Berry (1990, 1992), **berry_carnall_2006** (**berry_carnall_2006**), Ciliberto and Tamer (2009).

The second of the paper is to apply this model to study empirically the contribution of demand, cost, and strategic factors to explain why most companies in the US airline industry operate using **hub-and-spoke networks**. The model incorporates **different hypotheses** that have been suggested in the literature to explain **hub-and-spoke networks**. We estimate the model and use counterfactual experiments to obtain the contribution of demand, costs and strategic factors.

Hub-and-Spoke Networks

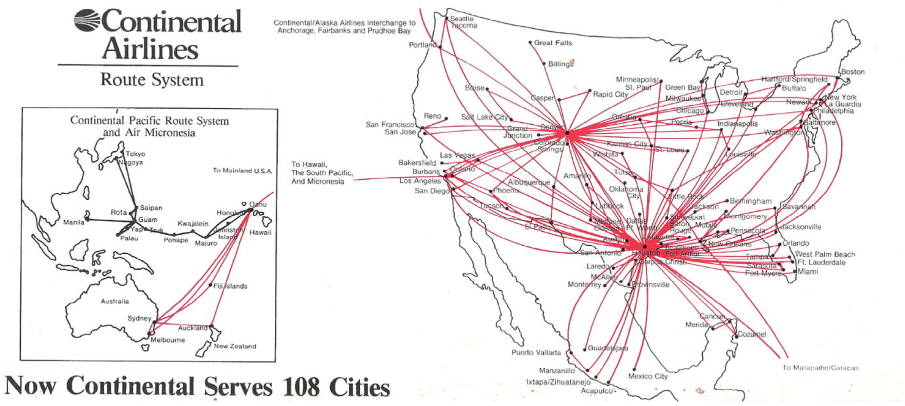

Figure 9.1: Hub & Spoke Networks: Continental route map in 1983

Hypotheses that have been suggested in the literature to explain airlines' adoption of hub-spoke networks:

- **Demand:** Travellers may be willing to pay for the services associated with an airline's scale of operation in an airport.

- **Costs:** Economies of scale at the plane level (marginal costs); Economies of scope at the airport level (fixed costs and entry costs); Contracts with airports (fixed costs and entry costs).

- **Strategic:** Entry deterrence (Hendricks, Piccione, and Tan ,1997).

The paper has several contributions to the literature on empirical dynamic games of oligopoly competition: (1) first application of dynamic network competition; (2) first paper to study empirically the strategic entry-deterrence aspect of hub-and-spoke networks; (3) first paper to apply the inclusive-values approach to a dynamic game; and (4) it proposes and implements a new method to make counterfactual experiments in dynamic games.

9.4.2 Model: Dynamic Game of Network Competition

N airlines and C cities, exogenously given. In our application, $N = 22$ and $C = 55$.

City-Pairs and Routes. Given the C cities, there are $M \equiv C(C-1)/2$ **non-directional city-pairs** (or markets). For each city-pair, an airline decides whether to operate non-stop flights. A **route** (or path) is a **directional round-trip between 2 cities**. A route may or may not have stops. A route-airline is a product, and there is a demand for each route-airline product. Airlines choose prices for each route they provide.

Networks. We index city-pairs by m, airlines by i, and time (quarters) by t. $x_{imt} \in \{0,1\}$ is a binary indicator for the event "airline i operates non-stop flights in city-pair m". $x_{it} \equiv \{x_{imt} : m = 1,2,...,M\}$ is the network of airline i at period t. The network x_{it} describes all the routes (products) that the airline provides, and whether they are non-stop or stop routes. The industry network is $x_t \equiv \{x_{it} : i = 1,2,...,N\}$.

Airlines' Decisions. An airline network x_{it} determines the set of routes (products) that the airline provides, that we denote by $L(x_{it})$. Every period, active airlines in a route compete in prices. Price competition determines variable profits for each airline. Every period (quarter), each airline decides also its network for next period. There is *time-to-build*. We represent this decision as $a_{it} \equiv \{a_{imt} : m = 1,2,...,M\}$, though $a_{imt} \equiv x_{imt+1}$.

Profit Function. The airline's total profit function is:

$$\begin{aligned} \Pi_{it} &= \sum_{r \in L(x_{it})} (p_{irt} - c_{irt}) q_{irt} \\ &- \sum_{m=1}^{M} a_{imt} \left(FC_{imt} + (1 - x_{imt})\, EC_{imt} \right) \end{aligned}$$

$(p_{irt} - c_{irt})q_{irt}$ is the variable profit in route r. FC_{imt} and EC_{imt} are fixed cost and entry cost in city-pair m.

Network effects in demand and costs. An important feature of the model is that demand, variable costs, fixed costs, and entry costs depend on the scale of operation (number of connections) of the airline in the origin and destination airports of the city-pair. Let HUB_{imt} be the "hub size" of airline i in market m at period t as measured by the total number of connections to other cities that airline i has in the origin and destination cities of market m at the beginning of period t. This is the most important endogeneous state variable of this model. It is endogenous because, though HUB_{imt} does not depend on the entry-exit decision of the airline in market m, a_{imt-1}, it does depend on the airline's entry-exit decisions in any other market that has common cities with market m, $\{a_{im't-1}$ for $m' \neq m$ and markets m' and m have common cities$\}$.

This implies that markets are interconnected through these hub-size effects. Entry-exit in a market has implications of profits in other markets. An equilibrium of this model is an equilibrium for the whole airline industry and not only for a single city-pair.

Dynamic Game / Strategy Functions. Airlines maximize intertemporal profits, are forward-looking, and take into account the implications of their entry-exit decisions on future profits and on the expected future reaction of competitors. Airlines' strategies depend only on payoff-relevant state variables, that is, Markov perfect equilibrium assumption. An airline's payoff-relevant information at quarter t is $\{x_t, \mathbf{z}_t, \varepsilon_{it}\}$. Let $\sigma \equiv \{\sigma_i(x_t, \mathbf{z}_t, \varepsilon_{it}) : i = 1,2,...,N\}$ be a set of strategy functions, one for each airline. A MPE is a set of strategy functions such that each airline's strategy maximizes the value of the airline for each possible state and taking as given other airlines' strategies.

9.4.3 Data

Airline Origin and Destination Survey (DB1B) collected by the Office of Airline Information of the BTS. Period 2004-Q1 to 2004-Q4. $C = 55$ largest metropolitan areas. $N = 22$ airlines. City Pairs: $M = (55 * 54)/2 = 1,485$.

Airlines: Passengers and Markets

	Airline (Code)	# Passengers (in thousands)	# City-Pairs in 2004-Q4 (maximum = 1,485)
1.	Southwest (WN)	25,026	373
2.	American (AA)(3)	20,064	233
3.	United (UA)(4)	15,851	199
4.	Delta (DL)(5)	14,402	198
5.	Continental (CO)(6)	10,084	142
6.	Northwest (NW)(7)	9,517	183
7.	US Airways (US)	7,515	150
8.	America West (HP)(8)	6,745	113
9.	Alaska (AS)	3,886	32
10.	ATA (TZ)	2,608	33
11.	JetBlue (B6)	2,458	22

Airlines, their Hubs, and Hub-Spoke Ratios

Airline (Code)	1st largest hub	Hub-Spoke Ratio (%) One Hub	2nd largest hub	Hub-Spoke Ratio (%) Two Hubs
Southwest	Las Vegas (35)	9.3	Phoenix (33)	18.2
American	Dallas (52)	22.3	Chicago (46)	42.0
United	Chicago (50)	25.1	Denver (41)	45.7
Delta	Atlanta (53)	26.7	Cincinnati (42)	48.0
Continental	Houston (52)	36.6	New York (45)	68.3
Northwest	Minneapolis (47)	25.6	Detroit (43)	49.2
US Airways	Charlotte (35)	23.3	Philadelphia (33)	45.3
America West	Phoenix (40)	35.4	Las Vegas (28)	60.2
Alaska	Seattle (18)	56.2	Portland (10)	87.5
ATA	Chicago (16)	48.4	Indianapolis (6)	66.6
JetBlue	New York (13)	59.0	Long Beach (4)	77.3

Figure 9.2: Cumulative Hub-and-Spoke Ratios

Distribution of Markets by Number of Incumbents	
Markets with 0 airlines	35.44%
Markets with 1 airline	29.06%
Markets with 2 airlines	17.44%
Markets with 3 airlines	9.84%
Markets with 4 or more airlines	8.22%

Number of Monopoly Markets by Airline	
Southwest	157
Northwest	69
Delta	56
American	28
Continental	24
United	17

Entry and Exit	
	All Quarters
Distribution of Markets by Number of New Entrants	
Markets with 0 Entrants	84.66%
Markets with 1 Entrant	13.37%
Markets with 2 Entrants	1.69%
Markets with 3 Entrants	0.27%
Distribution of Markets by Number of Exits	
Markets with 0 Exits	86.51%
Markets with 1 Exit	11.82%
Markets with 2 Exits	1.35%
Markets with more 3 or 4 Exits	0.32%

9.4.4 Specification and Estimation of Demand

Demand. Let $d \in \{0,1\}$ be the indicator of "direct" or non-stop flight. Let q_{irdt} be the number of tickets sold by airline i for route r, type of flight d, at quarter t. For a given route r and quarter t, the quantities $\{q_{irdt}$: for every airline i and $d = 0,1\}$ come from a system of demand of differentiated product. More specifically, we consider a Nested Logit demand. For notational simplicity, we omit here the subindexes (r,t), but the demand system refers to a specific route and quarter.

Let H be the number of travelers in the route. Each traveler in the route demands only one trip (per quarter) and chooses which product to purchase. The indirect utility of a traveler who purchases product (i,d) is $U_{id} = b_{id} - p_{id} + v_{id}$, where p_{id} is the price of product (i,d), b_{id} is the "quality" or willingness to pay for the product of the average consumer in the market, and v_{id} is a consumer-specific component that captures consumer heterogeneity in preferences. Product quality b_{ird} depends on exogenous characteristics of the airline and the route, and on the endogenous "hub-size" of the airline in the origin and destination airports.

$$b_{id} \quad = \quad \alpha_1 \, d + \alpha_2 \, HUB_i + \alpha_3 \, DIST + \xi_i^{(1)} + \xi^{(2)} + \xi_{id}^{(3)}$$

α_1 to α_3 are parameters. $DIST$ is the flown distance between the origin and destination cities of the route. $\xi_i^{(1)}$ is an airline fixed-effect that captures between-airlines differences in quality which are constant over time and across markets. $\xi^{(2)}$ represents the interaction of (origin and destination) city dummies and time dummies. These terms account for demand shocks, such as seasonal effects, which vary across cities and over time. $\xi_{id}^{(3)}$ is a demand shock that is airline and route specific. The variable HUB_i represents the "hub size" airline i in the origin and destination airports of the route r.

In the Nested Logit, we have that $v_{id} = \sigma_1\ v_i^{(1)} + \sigma_2\ v_{id}^{(2)}$, where $v_i^{(1)}$ and $v_{id}^{(2)}$ are independent Type I extreme value random variables, and σ_1 and σ_2 are parameters that measure the dispersion of these variables, with $\sigma_1 \geq \sigma_2$. A property of the nested logit model is that the demand system can be represented using the following closed-form demand equations:

$$\ln(s_{id}) - \ln(s_0) \quad = \quad \frac{b_{id} - p_{id}}{\sigma_1} + \left(1 - \frac{\sigma_2}{\sigma_1}\right)\ \ln\left(s_{id}^*\right) \tag{9.2}$$

where s_0 is the share of the outside alternative in route r, that is, $s_{0r} \equiv 1 - \sum_{i=1}^{N}(s_{ir0} + s_{ir1})$, and s_{id}^* is the market share of product (i,d) within the products of airline i in this route, that is, $s_{id}^* \equiv s_{id}/\left(s_{i0} + s_{i1}\right)$.

Therefore, we have the following demand regression equation:

$$\ln(s_{irdt}) - \ln(s_{0rdt}) \quad = \quad W_{irdt}\ \alpha + \left(\frac{-1}{\sigma_1}\right) p_{irdt} + \left(1 - \frac{\sigma_2}{\sigma_1}\right)\ \ln\left(s_{irdt}^*\right) + \xi_{irdt}^{(3)} \tag{9.3}$$

The regressors in vector W_{irdt} are: dummy for nonstop-flight, hub-size, distance, airline dummies, origin-city dummies $\times$ time dummies, and destination-city dummies $\times$ time dummies.

Issues: Is HUB_{irt} correlated with $\xi_{irdt}^{(3)}$? Are the BLP instruments (HUB size of competing airlines in route r at period t) valid in this equation, that is, are they correlated with $\xi_{irdt}^{(3)}$?

ASSUMPTION D1: Idiosyncratic demand shocks $\{\xi_{irdt}^{(3)}\}$ are not serially correlated over time.

ASSUMPTION D2: The idiosyncratic demand shock $\{\xi_{irdt}^{(3)}\}$ is private information of the corresponding airline. Furthermore, the demand shocks of two different airlines at two different routes are independently distributed.

Under assumption *D1*, the hub-size variable is not correlated with $\xi_{irdt}^{(3)}$ because HUB_{irt} is predetermined. Under assumption D2, HUB sizes of competing airlines in route r at period t are not correlated with $\xi_{irdt}^{(3)}$ and they are valid instruments for price p_{irdt}. Note that both assumptions D1 and D2 are testable. We can use the residuals of $\xi_{irdt}^{(3)}$ to test for no serial correlation (assumption D1) and no spatial correlation (assumption D2) in the residuals.

Table 7 presents estimates of the demand system.

Table 7
Demand Estimation[1]
Data: 85,497 observations. 2004-Q1 to 2004-Q4

	OLS		**IV**	
FARE (in $100) $\left(-\frac{1}{\sigma_1}\right)$	-0.329	(0.085)	-1.366	(0.110)
ln(s*) $\left(1-\frac{\sigma_2}{\sigma_1}\right)$	0.488	(0.093)	0.634	(0.115)
NON-STOP DUMMY	1.217	(0.058)	2.080	(0.084)
HUBSIZE-ORIGIN (in million people)	0.032	(0.005)	0.027	(0.006)
HUBSIZE-DESTINATION (in million people)	0.041	(0.005)	0.036	(0.006)
DISTANCE	0.098	(0.011)	0.228	(0.017)
σ_1 **(in $100)**	3.039	(0.785)	0.732	(0.059)
σ_2 **(in $100)**	1.557	(0.460)	0.268	(0.034)
Test of Residuals Serial Correlation **m1**$\sim N(0,1)$ **(p-value)**	0.303	(0.762)	0.510	(0.610)

(1) All the estimations include airline dummies, origin-airport dummies $\times$ time dummies, and destination-airport dummies $\times$ time dummies. Stadard errors in parentheses.

The most important result is that the effect of hub-size on demand is statistically significant but very small: on average consumers are willing to pay approx. $2 for an additional connection of the airline at the origin or destination airports ($\$2 \simeq \$100 * (0.027/1.366)$).

9.4.5 Specification and Estimation of Marginal Cost

Static Bertrand competition between airlines active in a route imply:

$$p_{irdt} - c_{irdt} = \frac{\sigma_1}{1 - \bar{s}_{irt}}$$

where $\bar{s}_{irt} = (e_{ir0t} + e_{ir1t})^{\sigma_2/\sigma_1} [1 + \sum_{j=1}^{N} (e_{jr0t} + e_{jr1t})^{\sigma_2/\sigma_1}]^{-1}$, $e_{irdt} \equiv \exp\{(b_{irdt} - p_{irdt})/\sigma_2\}$. Then, given the estimated demand parameters we can obtain estimates of the marginal costs c_{irdt}.

We are interested in estimating the effect of "hub-size" on marginal costs. We estimated the following model for marginal costs:

$$c_{irdt} \quad = \quad W_{irdt}\ \delta + \omega_{irdt}$$

where the regressors in vector W_{irdt} are: dummy for nonstop-flight, hub-size, distance, airline dummies, origin-city dummies $\times$ time dummies, and destination-city dummies $\times$ time dummies.

Again, under the assumption that the error term ω_{irdt} is not serially correlated, hub-size is an exogenous regressor and we can estimate the equation for marginal costs using OLS.

Table 8
Marginal Cost Estimation[1]
Data: 85,497 observations. 2004-Q1 to 2004-Q4
Dep. Variable: Marginal Cost in \$100

	Estimate	(Std. Error)
NON-STOP DUMMY	0.006	(0.010)
HUBSIZE-ORIGIN (in million people)	-0.023	(0.009)
HUBSIZE-DESTINATION (in million people)	-0.016	(0.009)
DISTANCE	5.355	(0.015)
Test of Residuals Serial Correlation		
m1 $\sim N(0,1)$ **(p-value)**	0.761	(0.446)

(1) All the estimations include airline dummies, origin-airport dummies $\times$ time dummies, and destination-airport dummies $\times$ time dummies.

Again, the most important result from this estimation is that the effect of hub-size on marginal cost is statistically significant but very small: on average an additional connection of the airline at the origin or destination airports implies a reduction in marginal cost between \$1.6 and \$2.3.

9.4.6 Simplifying assumptions for solution and estimation of dynamic game of network competition

The next step is the estimation of the effects if hub-size on fixed operating costs and sunk entry-costs. We consider the following structure in these costs.

$$\begin{aligned} FC_{imt} &= \gamma_1^{FC} + \gamma_2^{FC}\, HUB_{imt} + \gamma_3^{FC} DIST_m + \gamma_{4i}^{FC} + \gamma_{5c}^{FC} + \varepsilon_{imt}^{FC} \\ EC_{imt} &= \eta_1^{EC} + \eta_2^{EC}\, HUB_{imt} + \eta_3^{EC} DIST_m + \eta_{4i}^{EC} + \eta_{5c}^{EC} \end{aligned}$$

where γ_{4i}^{FC} and η_{4i}^{EC} are airline fixed effects, and γ_{5c}^{FC} and η_{5c}^{EC} are city (origin and destination) fixed effects. ε_{imt}^{FC} is a private information shock. The parameters in these functions are estimated using data on airlines entry-exit decisions and the dynamic game.

However, this dynamic game has really a large dimension. Given the number of cities and airlines in our empirical analysis, the number of possible industry networks is $|X| = 2^{NM} \simeq 10^{10,000}$ (much larger than all the estimates of the number of atoms in the observable universe, around 10^{100}). We should make simplifying assumptions.

We consider **two types of simplifying assumptions** that reduce the dimension of the dynamic game and make its solution and estimation manageable.

1. An **airline's choice of network is decentralized** in terms of the separate decisions of local managers.

2. The state variables of the model can be aggregated in a vector of **inclusive-values** that belongs to a space with a much smaller dimension than the original state space.

(1) **Decentralizing the Airline's Choice of Network.** Each airline has M local managers, one for each city-pair. A local manager decides whether to operate or not non-stop flights in her local-market: that is, she chooses a_{imt}. The private information shock ε_{imt}^{FC} is private information of the manager (i,m).

IMPORTANT: A local manager is not only concerned about profits in her own route. She internalizes the effects of her own entry-exit decision in many other routes. This is very important to allow for entry deterrence effects of hub-and-spoke networks.

ASSUMPTION: Let R_{imt} be the sum of airline i's variable profits over all the routes that include city-pair m as a segment. *Local managers maximize the expected and discounted value of*

$$\Pi_{imt} \equiv R_{imt} - a_{imt} \left(FC_{imt} + (1 - x_{imt}) EC_{imt} \right).$$

(2) Inclusive-Values. Decentralization of the decision simplifies the computation of players' best responses, but the state space of the decision problem of a local manager is still huge. Notice that the profit of a local manager depends only on the state variables:

$$\mathbf{x}_{imt}^{*} \equiv (x_{imt},\ R_{imt},\ HUB_{imt})$$

ASSUMPTION: The *vector* $\mathbf{x}_{imt}^{*}$ *follows a controlled first-order Markov Process:*

$$\Pr\left(\mathbf{x}_{im,t+1}^{*} \mid \mathbf{x}_{imt}^{*}, a_{imt}, \mathbf{x}_t, \mathbf{z}_t\right) = \Pr\left(\mathbf{x}_{im,t+1}^{*} \mid \mathbf{x}_{imt}^{*}, a_{imt}\right)$$

A MPE of this game can be describe as a vector of probability functions, one for each local-manager:

$$P_{im}(\mathbf{x}_{imt}^{*}) : i = 1,2,...,N;\ m = 1,2,...,M$$

$P_{im}(\mathbf{x}_{imt}^{*})$ is the probability that local-manager (i,m) decides to be active in city-pair m given the state $\mathbf{x}_{imt}^{*}$. An equilibrium exists. The model typically has multiple equilibria.

9.4.7 Estimation of dynamic game of network competition

We use the Nested Pseudo Likelihood (NPL) method.

Table 9
Estimation of Dynamic Game of Entry-Exit[1]
Data: 1,485 markets $\times$ 22 airlines $\times$ 3 quarters $=$ 98,010 observations

	Estimate (Std. Error) (in thousand \$)
Fixed Costs (quarterly):[2]	
$\gamma_1^{FC} + \gamma_2^{FC}$**mean hub-size** $+\gamma_3^{FC}$**mean distance (average fixed cost)**	119.15 (5.233)
γ_2^{FC} **(hub-size in # cities connected)**	-1.02 (0.185)
γ_3^{FC} **(distance, in thousand miles)**	4.04 (0.317)
Entry Costs:	
$\eta_1^{EC} + \eta_2^{EC}$**mean hub-size** $+\eta_2^{EC}$**mean distance (average entry cost)**	249.56 (6.504)
η_2^{EC} **(hub-size in # cities connected)**	-9.26 (0.140)
η_3^{EC} **(distance, in thousand miles)**	0.08 (0.068)
σ_ε	8.402 (1.385)
β	0.99 (not estimated)
Pseudo R-square	0.231

(1) All the estimations include airline dummies, and city dummies.

(2) Mean hub size = 25.7 million people. Mean distance (nonstop flights) = 1996 miles

- Goodness of fit:

Table 10
Comparison of Predicted and Actual Statistics of Market Structure
1,485 city-pairs (markets). Period 2004-Q1 to 2004-Q4

		Actual (Average All Quarters)	Predicted (Average All Quarters)
	Herfindahl Index (median)	5338	4955
Distribution of Markets by Number of Incumbents	Markets with 0 airlines	35.4%	29.3%
	" " 1 airline	29.1%	32.2%
	" " 2 airlines	17.4%	24.2%
	" " 3 airlines	9.8%	8.0%
	" " $\geq$4 airlines	8.2%	6.2%
Number (%) of Monopoly Markets for top 6 Airlines	Southwest	151 (43.4%)	149 (38.8%)
	Northwest	66 (18.9%)	81 (21.1%)
	Delta	57 (16.4%)	75 (19.5%)
	American	31 (8.9%)	28 (7.3%)
	Continental	27 (7.7%)	27 (7.0%)
	United	16 (4.6%)	24 (6.2%)
Distribution of Markets by Number of New Entrants	Markets with 0 Entrants	84.7%	81.9%
	" " 1 Entrant	13.4%	16.3%
	" " 2 Entrants	1.7%	1.6%
	" " $\geq$3 Entrants	0.3%	0.0%
Distribution of Markets by Number of Exits	Markets with 0 Exits	86.5%	82.9%
	" " 1 Exit	11.8%	14.6%
	" " 2 Exits	1.4%	1.4%
	" " $\geq$3 Exits	0.3%	0.0%

9.4.8 Counterfactual Experiments

To deal with multiple equilibria or equilibrium selection in the counterfactual experiment, we use the homotopy method that we saw in the previous chapter.

Table 11
Counterfactual Experiments
Hub-and-Spoke Ratios when Some Structural Parameters Become Zero

		Method 1: Taylor Approximation			
Carrier	Observed	**Experiment 1** No hub-size effects in variable profits	**Experiment 2** No hub-size effects in fixed costs	**Experiment 3** No hub-size effects in entry costs	**Experiment 4** No complementarity across markets
Southwest	18.2	17.3	15.6	8.9	16.0
American	42.0	39.1	36.5	17.6	29.8
United	45.7	42.5	39.3	17.8	32.0
Delta	48.0	43.7	34.0	18.7	25.0
Continental	68.3	62.1	58.0	27.3	43.0
Northwest	49.2	44.3	36.9	18.7	26.6
US Airways	45.3	41.7	39.0	18.1	34.4

		Method II: Policy Iterations Starting from Taylor Approx.			
Carrier	Observed	**Experiment 1** No hub-size effects in variable profits	**Experiment 2** No hub-size effects in fixed costs	**Experiment 3** No hub-size effects in entry costs	**Experiment 4** No complementarity across markets
Southwest	18.2	16.9	14.4	8.3	16.5
American	42.0	37.6	34.2	16.6	24.5
United	45.7	40.5	37.3	15.7	30.3
Delta	48.0	41.1	32.4	17.9	22.1
Continental	68.3	60.2	57.4	26.0	42.8
Northwest	49.2	40.8	35.0	17.2	23.2
US Airways	45.3	39.7	37.1	16.4	35.2

Experiment 1: Counterfactual model: $\alpha_2 = \alpha_3 = \delta_2 = \delta_3 = 0$
Experiment 2: Counterfactual model: $\gamma_2^{FC} = 0$
Experiment 3: Counterfactual model: $\eta_2^{EC} = 0$
Experiment 4: Counterfactual model: Variable profit of local manager in city-pair AB includes only variable profits from non-stop routes AB and BA.

Main results:

-Hub-size effects on **demand, variable costs and fixed operating costs** are significant but can **explain very little of the propensity to adopt hub-spoke networks**.

- **Hub-size effects on Sunk Entry Costs are large**. This is the most important factor to explain hub-spoke networks.

- **Strategic factors: hub-spoke network as a strategy to deter entry** is the second most important factor for some of the largest carriers (Northwest and Delta).

9.5 Dynamic strategic behavior in firms' innovation

9.5.1 Competition and Innovation: static analysis

Competition and Innovation. Long lasting debate on the effect of competition on innovation (for instance, Schumpeter, Arrow). Apparently, there are contradictory results between a good number of theory papers showing that "competition" has a negative effect on innovation (**dasgupta_stiglitz_1980** ,**dasgupta_stiglitz_1980**; **spence_1984** ,**spence_1984**), and a good number of reduced-form empirical papers showing a positive relationship between measures of competition and measures of innovation (**porter_1990** ,**porter_1990**; **geroski_1990** ,**gerosk_1990**; **blundell_griffith_1999** ,**blundell_griffith_1999**). Vives (2008) presents a systematic theoretical analysis of this problem that tries to explain the apparent disparities between existing theoretical and empirical results.

Competition and Innovation: Vives (2008) considers:

[1] Different sources of exogenous increase in competition. (i) reduction in entry cost; (ii) increase in market size; (iii) increase in degree of product substitutability.

[2] Different types of innovation. (i) process or cost-reduction innovation; (ii) product innovation / new products.

[3] Different models of competition and specifications. (i) Bertrand; (ii) Cournot

[4] Specification of demand. linear, CES, exponential, logit, nested logit.

Vives shows that [1] the form of increase in competition; and [2] the type of innovation are key to determine a positive or a negative relationship between competition and innovation. However, the results are very robust to: [3] the form of competition (Bertrand or Cournot) and [4] the specification of the demand system.

Model. Static model with symmetric firms, endogenous entry. Profit of firm i: $\pi_j = [p_j - c(z_j)]\ s\ d(p_j, p_{-j}, n; \alpha) - z_j - F$, $s =$ market size; $n =$ number of firm; $d(p_j, p_{-j}, n; \alpha) =$ demand per-consumer; $\alpha =$ degree of substitutability; $c(z_j) =$ marginal cost (constant); $z_i =$ expenditure in cost reduction; $c' < 0$ and $c'' > 0$; $F =$ entry cost.

Equilibrium. Nash equilibrium for simultaneous choice of (p_j, z_j). Symmetric equilibrium. There is endogenous entry. Marginal condition w.r.t cost-reduction R&D (z) is: $-c'(z)\ s\ d(p,n;\alpha) - 1 = 0$. Since $c'' > 0$, this implies $z = g(s\ d(p,n;\alpha))$, where g is an increasing function. The incentive to invest in cost reduction increases with output per firm, $q \equiv s\ d(p,n;\alpha)$.

Any exogenous change in competition (say in α, s, or F) has three effects on output per firm and therefore on investment in cost-reduction R&D.

$$\frac{dz}{d\alpha} = g'(q)\left[\frac{\partial\,[s\ d(p,n;\alpha)]}{\partial\alpha} + \frac{\partial\,[s\ d(p,n;\alpha)]}{\partial p}\frac{\partial p}{\partial\alpha} + \frac{\partial\,[s\ d(p,n;\alpha)]}{\partial n}\frac{\partial n}{\partial\alpha}\right]$$

$\dfrac{\partial\left[s\, d(p,n;\alpha)\right]}{\partial \alpha}$ is the **direct demand effect,** $\dfrac{\partial\left[s\, d(p,n;\alpha)\right]}{\partial p}\dfrac{\partial p}{\partial \alpha}$ is the **price pressure effect,** $\dfrac{\partial\left[s\, d(p,n;\alpha)\right]}{\partial n}\dfrac{\partial n}{\partial \alpha}$ is the **number of entrants effect.** The effects of different changes in competition on cost-reduction R&D can be explained in terms of these three effects.

Summary of comparative statics. **(i) Increase in market size.** - Increases per-firm expenditures in cost-reduction; - Effect on product innovation (# varieties) can be either positive or negative. **(ii) Reduction in cost of market entry.** - Reduces per-firm expenditures in cost-reduction; - Increases number of firms and varieties. **(iii) Increase in degree of product substitution.** - Increases per-firm expenditures in cost-reduction; - # varieties may increase or decline.

Some limitations in this analysis. The previous analysis is static, without uncertainty, with symmetric and single product firms. Therefore, the following factors that relate competition and innovation are absent from the analysis. (1) **Preemptive motives.** (2) **Cannibalization of own products**. (3) **Increasing uncertainty** in returns to R&D due competition (asymmetric info**)**. To study these factors, we need dynamic games with uncertainty, and asymmetric multi-product firms.

9.5.2 Creative destruction: incentives to innovate of incumbents and new entrants

Innovation and creative destruction (Igami ,2017). Innovation, the creation of new products and technologies, necessarily implies the "destruction" of existing products, technologies, and firms. In other words, the survival of existing products / technologies / firms is at the cost of preempting the birth of new ones. The speed (and the effectiveness) of the innovation process in an industry depends crucially on the dynamic strategic interactions between "old" and "new" products/technologies. Igami (2017) studies these interactions in the context of the Hard-Disk-Drive (HDD) industry during 1981-1998.

HDD: Different generations of products

HDD: Different generations of products

Adoption new tech: Incumbents vs. New Entrants

Adoption new tech: Incumbents vs. New Entrants. Igami focuses on the transition from 5.25 to 3.5 inch products. He consider three main factors that contribute to the relative propensity to innovate of incumbents and potential entrants. **Cannibalization.** For incumbents, the introduction of a new product reduces the demand for their pre-existing products. **Preemption.** Early adoption by incumbents can deter entry and competition from potential new entrants. **Differences in entry/innovation costs.** It can play either way. Incumbents have knowledge capital and **economies of scope**, but they also have **organizational inertia**.

Data. **Market shares: New/Old products**

Average Prices: New/Old products

Average Quality: New/Old products

Market Structure: New/Old products

Model. Market structure at period t is described by four type of firms according to the products they produce: $s_t = \{N_t^{old}, N_t^{both}, N_t^{new}, N_t^{pe}\}$

• Initially, $N_0^{both} = N_0^{new} = 0$. Timing within a period t:

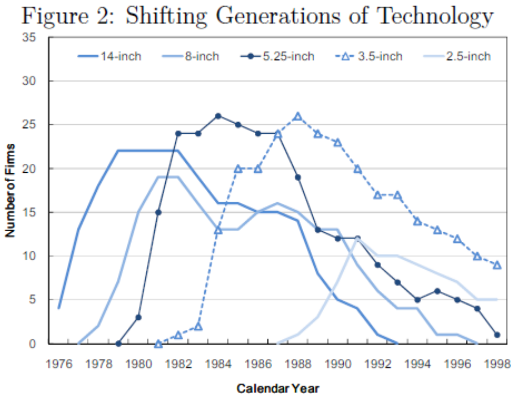

Figure 9.3: Hard drives: Different generations of products

1 Incumbents compete (à la Cournot) $\rightarrow$ Period profits $\pi_t(s_{it}, s_{-it})$

2. The $N_t^{o\ell d}$ firms draw private info shocks and simultaneously choose $a_{it}^{o\ell d} \in \{exit, stay, innovate\}$

3. The N_t^{both} observe $a_t^{o\ell d}$, draw private info shocks, and simultaneously choose $a_{it}^{both} \in \{exit, stay\}$

4. The N_t^{new} observe $a_t^{o\ell d}$, a_t^{both},draw private info shocks, and simultaneously choose $a_{it}^{new} \in \{exit, stay\}$

5. The N_t^{pe} observe $a_t^{o\ell d}$, a_t^{both}, a_t^{new}, draw private info shocks, and simultaneously choose $a_{it}^{pe} \in \{entry, noentry\}$.

Given these choices, next period market structure is obtained, s_{t+1}, and demand and cost variables evolve exogenously. Why imposing this order of move? This Assumption, together with: - Finite horizon T; Homogeneous firms (up to the i.i.d. private info

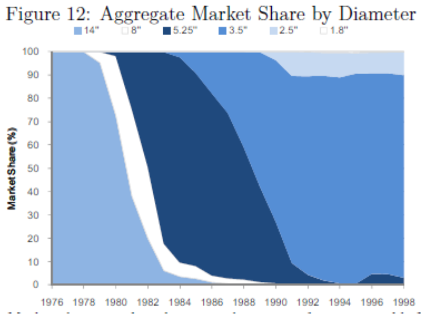

Figure 9.4: Hard drives: Different generations of products

shocks) within each type, implies that there is a **unique Markov Perfect equilibrium**. This is very convenient for estimation (Igami uses a standard/Rust Nested Fixed Point Algorithm for estimation) and especially for counterfactuals.

Demand. Simple logit model of demand. A product is defined as a pair {technology, quality}, where technology $\in \{o\ell d, new\}$ and quality represents different storage sizes. There is no differentiation across firms (perhaps true, but assumption comes from data limitations).

Estimation:

$$\ln\left(\frac{s_j}{s_k}\right) = \alpha_1 \left[p_j - p_k\right] + \alpha_2 \left[1_j^{new} - 1_k^{new}\right] + \alpha_3 \left[x_j - x_k\right] + \xi_j - \xi_k$$

Data: multiple periods and regions. IVs: Hausman-Nevo. Prices in other regions.

Estimates of Demand

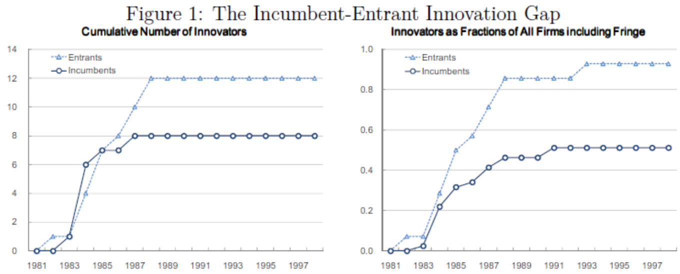

Figure 9.5: Adoption Propensity: Incumbents vs. New Entrants

Evolution of unobserved Quality (epsi)

Evolution of Marginal Costs

Evolution of Period Profits [keeping market structure]

Estimates of Dynamic Parameters

Estimates of Dynamic Parameters

Different estimates depending on the order of move within a period. Cost for innovation is smaller for incumbents than for new entrants ($\kappa^{inc} < \kappa^{pe}$). Organizational inertia does not seem an important factor. Magnitude of entry costs are comparable to the annual R&D budget of specialized HDD manufacturers, for instance, Seagate Tech: between $\$0.6B - \$1.6B$.

Estimated Model: Goodness of fit

Counterfactual: Removing Cannibalization

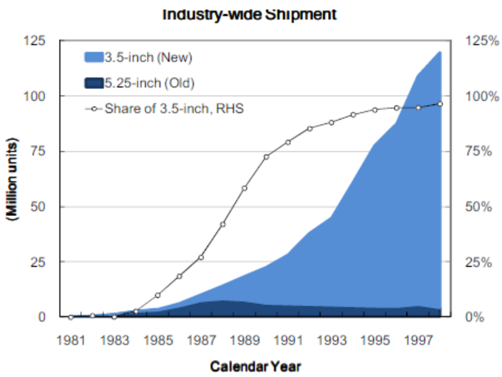

Figure 9.6: Market shares New/Old products

Counterfactual: Removing Preemption

9.5.3 Competition and innovation in the CPU industry: Intel and AMD

Studies competition between Intel and AMD in the PC microprocessor industry. Incorporates durability of the product as a potentially important factor. Two forces drive innovation: - competition between firms for the technological frontier; - since PCs have little physical depreciation, firms have the incentive to innovate to generate a technological depreciation of consumers' installed PCs that encourages them to upgrade [most of the demand during the period $> 89\%$ was upgrading]. Duopolists face both forces, whereas a monopolist faces only the latter (but in a stronger way).

The PC microprocessor industry. Very important to the economy: - Computer equipment manufacturing industry generated 25% of U.S. productivity growth from

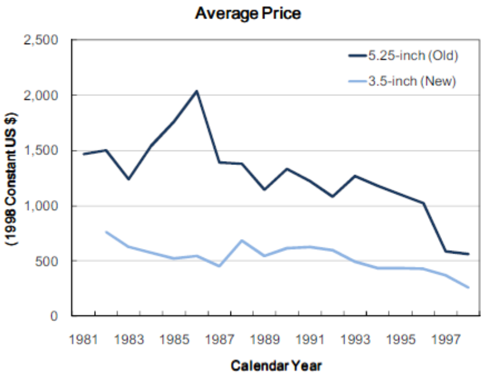

Figure 9.7: Average Prices: New/Old products

1960 to 2007. - Innovations in microprocessors are directly measured via improved performance on benchmark tasks. Most important: CPU speed. Interesting also from the point of view of antitrust: - In 2004: several antitrust lawsuits claiming Intel's anticompetitive practices, for instance, rewarding PC manufacturers that exclusively use Intel microprocessors. - Intel foreclosures AMD to access some consumers.- Intel settled these claims in 2009 with a $1.25 billion payment to AMD.

Market is essentially a duopoly, with AMD and Intel selling 95% CPUs. Firms have high R&D intensities, R&D/Revenue (1993-2004): - AMD 20% ; and Intel 11%. Innovation is rapid: new products are released nearly every quarter. CPU performance (speed) doubles every 7 quarters, that is, Moore's law. AMD and Intel extensively cross-license each other's technologies, that is, positive spillovers.

As microprocessors are durable, replacement drives are important part of demand.

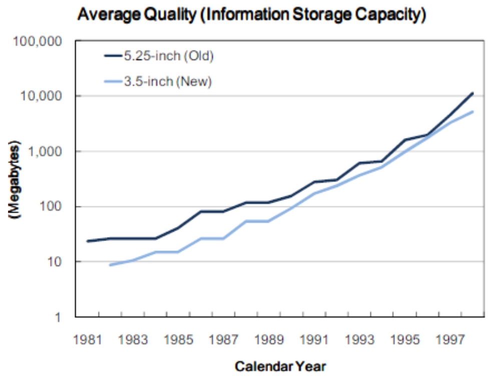

Figure 9.8: Average Quality: New/Old products

The importance of replacement is partly exogenous (new consumers arriving to the marker), and partly endogenous: speed of improvements in frontier microprocessors that encourages consumers to upgrade. In 2004, 82% of PC purchases were replacements. After an upgrade boom, prices and sales fall as replacement demand drops. Firms must continue to innovate to rebuild replacement demand.

Data. Proprietary data from a market research firm specializing in the microprocessor industry. Quarterly data from Q1-1993 to Q4-2004 (48 quarters). Information on: shipments in physical units for each type of CPU; manufacturers' average selling prices (ASP); **production costs**; CPU characteristics (speed). All prices and costs are converted to base year 2000 dollars. Quarterly R&D investment levels, obtained from firms' annual reports.

Moore's Law. Intel cofounder Gordon Moore predicted in 1965 that the number

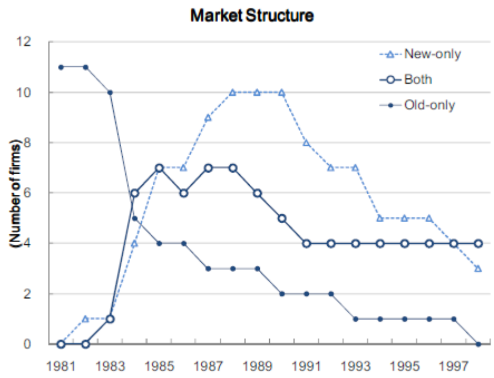

Figure 9.9: Market Structure: New/Old products

of transistors in a CPU (and therefore the CPU speed) would double every 2 years. Following figure shows "Moore's law" over the 48 quarters in the data. Quality is measured using processor speed. Quarterly % change in CPU speed is 10.2% for Intel and 11% for AMD.

Moore's Law (Frontier CPU speed)

Differential log-quality between Intel and AMD. Intel's initial quality advantage is moderate in 1993–94. Then, it becomes large in 1995-96 when Intel releases the Pentium. AMD's responded in 1997 introducing the K6 processor that narrows the gap. But parity is not achieved until the mid-2000 when AMD released the Athlon.

Model: General features. Dynamic model of an oligopoly with differentiated and durable products. Each firm j sells a single product and invests in R&D to improve its quality. If investments are successful, quality improves next quarter by a fixed proportion

Market definition:	Broad		Narrow	
Estimation method:	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Price ($000)	-1.66^{***}	-2.99^{***}	$-.93^{**}$	-3.28^{***}
	(.45)	(.55)	(.46)	(.63)
Diameter = 3.5-inch	$.84^{*}$	.75	1.75^{***}	$.91^{**}$
	(.46)	(.45)	(.31)	(.38)
Log Capacity (MB)	.18	$.87^{***}$	.04	1.20^{***}
	(.33)	(.27)	(.26)	(.31)
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*
Region/user dummies	–	–	*Yes*	*Yes*
Adjusted R^2	.43	.33	.50	.28
Number of obs.	176	176	405	405
Partial R^2 for Price	–	.32	–	.16
P-value	–	.00	–	.00

Figure 9.10: Estimates of Demand

δ; otherwise it is unchanged: log quality $q_{jt} \in \{0, \delta, 2\delta, 3\delta, \dots\}$. Consumers: a key feature of demand for durable goods is that the value of the no-purchase option is endogenous, determined by last purchase. The distribution of currently owned products by consumers is represented by the vector Δ_t. Δ_t affects current consumer demand. [Details]

Firms and consumers are forward looking. A consumer's i state space consists of $(q^*_{it}, q_t, \Delta_t)$: - q^*_{it} = the quality of her currently owned product q^*_t; - q_t = vector of firms' current qualities q_t; - Δ_t = distribution of qualities of consumers currently owned products. Δ_t is part of the consumers' state space because it affects expectations on future prices. State space for firms is (q_t, Δ_t). Given these state variables firms simultaneously choose prices p_{jt} and investment x_{jt}.

Consumer Demand. Authors: *"We restrict firms to selling only one product because*

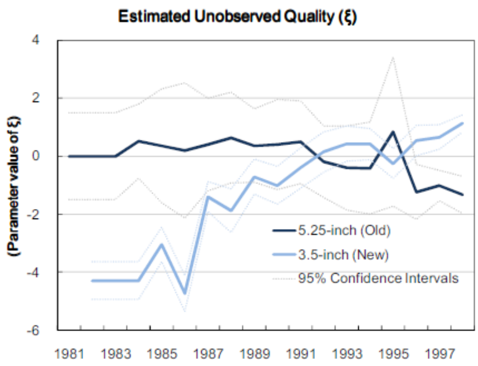

Figure 9.11: Evolution of unobserved Quality (epsi)

the computational burden of allowing multiproduct firms is prohibitive". Consumers own no more than one microprocessor at a time. Utility for a consumer i from firm j's new product with quality q_{jt} is given by: $u_{ijt} = \gamma\, q_{jt} - \alpha\ p_{jt} + \xi_j + \varepsilon_{ijt}$. Utility from the no-purchase option is: $u_{i0t} = \gamma\, q^*_{it} + \varepsilon_{i0t}$. A consumer maximizes her intertemporal utility given her beliefs about the evolution of future qualities and prices given (q_t, Δ_t).

Market shares for consumers currently owning q^* are:

$$s_{jt}(q^*) = \frac{\exp\{v_j(q_t, \Delta_t, q^*)\}}{\sum_{k=0}^{J} \exp\{v_k(q_t, \Delta_t, q^*)\}}$$

Using Δ_t to integrate over the distribution of q^* yields the market share of product j.

$$s_{jt}(q^*) = \sum_{q^*} s_{jt}(q^*)\ \Delta_t(q^*)$$

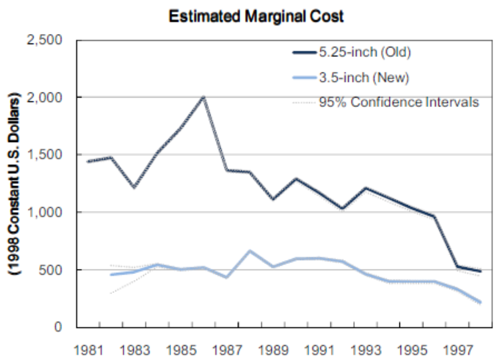

Figure 9.12: Evolution of Marginal Costs

Transition rule of Δ_t. By definition, next period Δ_{t+1} is determined by a known closed-form function of Δ_t, q_t, and s_t.

$$\Delta_{t+1} = F_\Delta(\Delta_t, q_t, s_t)$$

The period profit function is:

$$\pi_j(p_t, q_t, \Delta_t) = M\ s_j(p_t, q_t, \Delta_t)\ \left[p_{jt} - mc_j(q_{jt})\right]$$

The specification of the marginal cost is:

$$mc_j(q_{jt}) = \lambda_{0j} - \lambda_1(q_t^{\max} - q_{jt})$$

Marginal costs are smaller for non-frontier firms. Parameter λ_1 captures an spillover effect from the innovation of other firms.

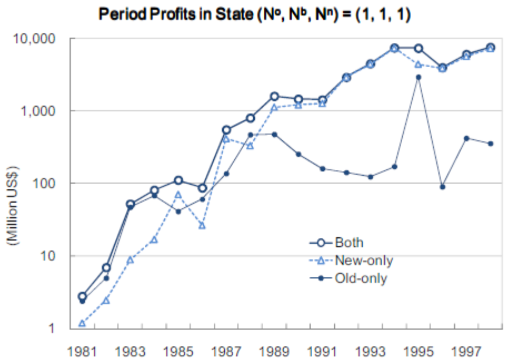

Figure 9.13: Evolution of Period Profits [keeping market structure]

Model: Firms. Innovation process. Relationship between investment in R&D (x_{jt}) and log-quality improvement ($\Delta q_{jt+1} = q_{jt+1} - q_{jt}$). Log-Quality improvement can take two values, 0 or δ. The probability that $\Delta q_{jt+1} = \delta$ is (Pakes and McGure, 1994):

$$\chi_j(x_{jt}, q_{jt}) = \frac{a_j(q_{jt})\, x_{jt}}{1 + a_j(q_{jt})\, x_{jt}}$$

$a_j(q_{jt})$ is the "investment efficiency" function. It is a decreasing function, to capture the idea of an increasing difficulty of advancing the frontier relative to catching up.

Let $W_j(q_t, \Delta_t)$ be the value function. The Bellman equation is:

$$W_j(q_t, \Delta_t) = \max_{x_{jt}, p_{jt}} \left[\pi_j(p_t, q_t, \Delta_t) - x_{jt} + \beta\ \mathbb{E}_t \left[W_j(q_{t+1}, \Delta_{t+1}) \right] \ \right]$$

The decision variables are continuous, and the best response function should satisfy the

Table 4: Estimates of the Dynamic Parameters

(\$ Billion)	Maximum Likelihood Estimates		
	(1)	(2)	(3)
Assumed order of moves:	Old-Both-New-PE	PE-New-Both-Old	PE-Old-Both-New
Fixed cost of operation (ϕ)	0.1474	0.1472	0.1451
	$[-0.02,\ 0.33]$	$[-0.02,\ 0.33]$	$[-0.03,\ 0.33]$
Incumbents' sunk cost (κ^{inc})	1.2439	1.2370	1.2483
	$[0.51,\ 2.11]$	$[0.50,\ 2.10]$	$[0.51,\ 2.11]$
Entrants' sunk cost (κ^{ent})	2.2538	2.2724	2.2911
	$[1.74,\ 2.85]$	$[1.76,\ 2.87]$	$[1.78,\ 2.89]$
Log likelihood	-112.80	-112.97	-113.46

Figure 9.14: Estimates of Dynamic Parameters

F.O.C.

$$
\begin{aligned}
\frac{\partial \pi_{jt}}{\partial p_{jt}} + \beta \frac{\partial \mathbb{E}_t \left[W_{j,t+1}\right]}{\partial p_{jt}} &= 0 \\
\frac{\partial \pi_{jt}}{\partial x_{jt}} - 1 + \beta \frac{\partial \mathbb{E}_t \left[W_{j,t+1}\right]}{\partial x_{jt}} &= 0
\end{aligned}
$$

Markov Perfect Equilibrium. (1) firms' and consumers' equilibrium strategies depend only on current payoff relevant state variables (q_t, Δ_t). (2) consumers have rational expectations about firms' policy functions. (3) each firm has rational expectations about competitors' policy functions and about the evolution of the ownership distribution.

Estimation. Marginal cost parameters (λ_0, λ_1) are estimated in a first step because the dataset includes data on marginal costs. The rest of the structural parameters, $\theta = (\gamma,$

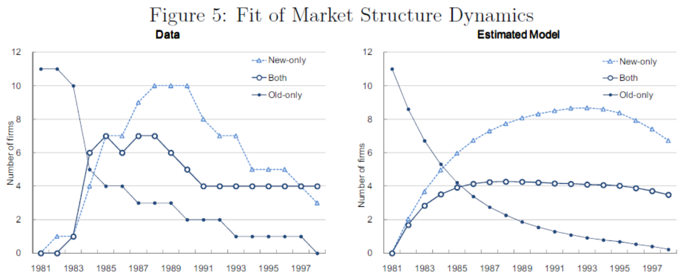

Figure 9.15: Estimated Model: Goodness of fit

α, ξ_{intel}, ξ_{amd}, $a_{0,intel}$, $a_{0,amd}$, a_1). Demand: γ, α, ξ_{intel}, ξ_{amd}; Investment innovation efficiency: $a_{0,intel}$, $a_{0,amd}$, a_1. θ is estimated using Indirect Inference or Simulated Method of Moments (SMM).

Moments to match: Mean of innovation rates $q_{j,t+1} - q_{jt}$ for each firm. Mean R&D intensities $x_{jt}/revenue_{jt}$ for each firm. Mean of differential quality $q_{intel,t} - q_{amd,t}$, and share of quarters with $q_{intel,t} \geq q_{amd,t}$. Mean of gap $q_t^{\max} - \overline{\Delta}_t$. Average prices, and OLS estimated coefficients of the regressions of p_{jt} on $q_{intel,t}$, $q_{amd,t}$, and average $\overline{\Delta}_t$. OLS estimated coefficients of the regression of $s_{intel,t}$ on $q_{intel,t} - q_{amd,t}$.

Empirical and predicted moments

Demand: Dividing γ by α: consumers are willing to pay \$21 for enjoying during 1 quarter a $\delta = 20\%$ increase in log quality. Dividing $\xi_{intel} - \xi_{amd}$ by α: consumers are willing to pay \$194 for Intel over AMD. The model needs this strong brand effect to

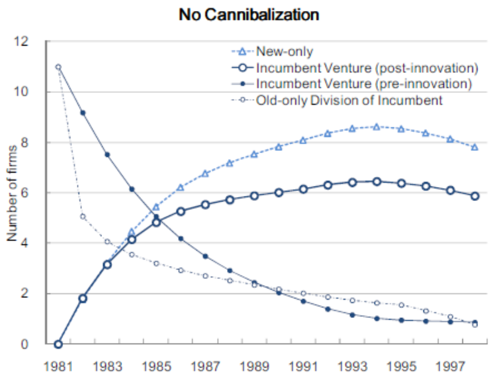

Figure 9.16: Counterfactual: Removing Cannibalization

explain the fact that AMD's share never rises above 22 percent in the period during which AMD had a faster product. Intel and AMD's innovation efficiencies are estimated to be .0010 and .0019, respectively, as needed for AMD to occasionally be the technology leader while investing much less.

Counterfactuals

From current duopoly (1) to Intel Monopoly (3) Innovation rate increases from 0.599 to 0.624. Mean quality upgrade increases 261% to 410%. Investment in R&D: increases by 1.2B per quarter: more than doubles. Price increases in \$102 (70%). Consumer surplus declines in \$121M (4.2%). Industry profits increase in \$159M. Social surplus increases in \$38M (less than 1%)

From current duopoly (1) to symmetric duopoly (2) Innovation rate declines from 0.599 to 0.501. Mean quality declines from 261% to 148%. Investment in R&D:

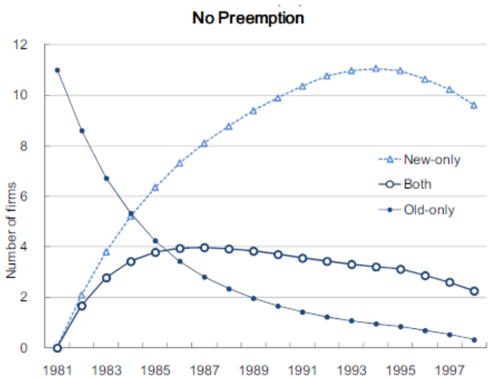

Figure 9.17: Counterfactual: Removing Preemption

declines by $178M$ per quarter. Price declines in \$48 (24%). Consumer surplus increases in \$$34M$ (1.2%). Industry profits decline in \$$8M$. Social surplus increases in \$$26M$ (less than 1%)

From current scenario (1) to myopic pricing. It reduces prices, increases CS, and reduces firms' profits. Innovation rates and investment in R&D decline dramatically. Why? Higher prices induce firms to innovate more rapidly. Prices are higher with dynamic pricing because firms want to preserve future demand.

The finding that innovation by a monopoly exceeds that of a duopoly reflects two features of the model: the monopoly must innovate to induce consumers to upgrade; the monopoly is able to extract much of the potential surplus from these upgrades because of its substantial pricing power. If there were a steady flow of new consumers into the market, such that most demand were not replacement, the monopoly would reduce

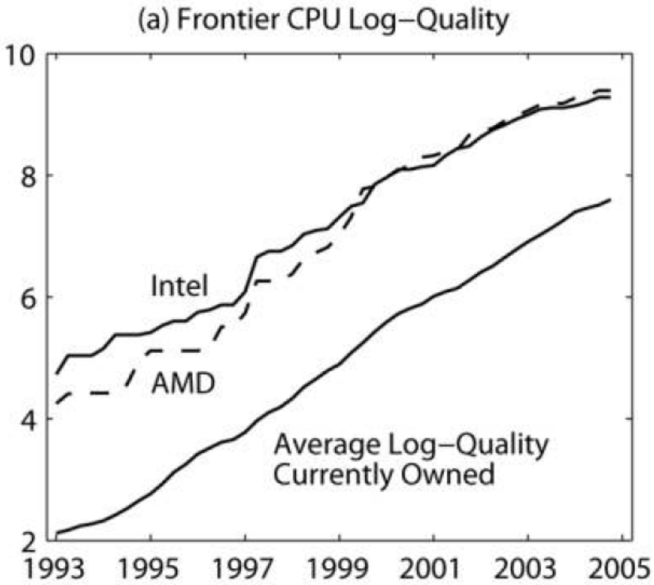

Figure 9.18: Moore's Law (Frontier CPU speed)

innovation below that of the duopoly.

Counterfactuals: Foreclosure. In 2009, Intel paid AMD $1.25 billion to settle claims that Intel's anticompetitive practices foreclosed AMD from many consumers. To study the effect of such practices on innovation, prices, and welfare, the authors perform a series of counterfactual simulations in which they vary the portion of the market to which Intel has exclusive access. Let ζ be the proportion of foreclosure market. Intel market share becomes: $s_j^* = \zeta\ \widehat{s}_j + (1-\zeta)\ s_j$, where s_j is the market share when AMD is competing, and $\widehat{s}_j$ is the market share when Intel competes only with the outside alternative.

Counterfactuals: Foreclosure

Margins monotonically rise steeply. Innovation exhibits an inverted U with a peak at $\zeta = 0.5$. Consumer surplus is actually higher when AMD is barred from a portion

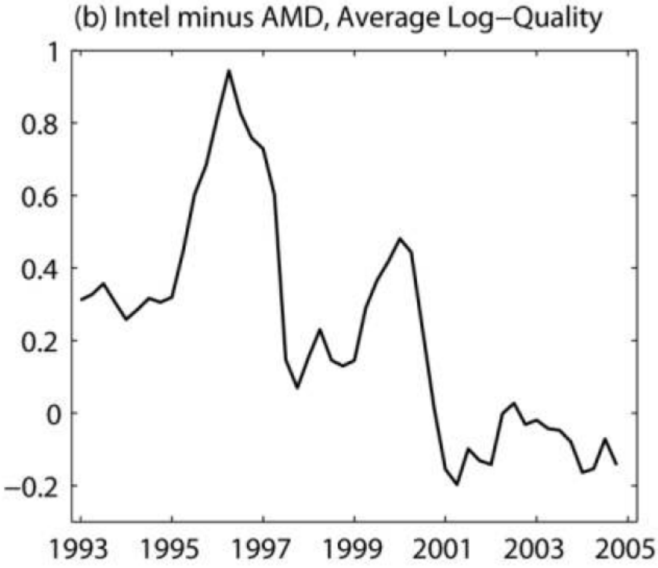

Figure 9.19: Differential log-quality between Intel and AMD

of the market, peaking at 40% foreclosure. This finding highlights the importance of accounting for innovation in antitrust policy: the decrease in consumer surplus from higher prices can be more than offset by the compounding effects of higher innovation rates.

Counterfactuals: Product substitutability

Innovation in the monopoly exhibits an inverted U as substitutability increases. Innovation in the duopoly increases as substitutability increases until Var( ) becomes too small for firms with similar qualities to coexist. - Beyond this "shakeout" threshold, the laggard eventually concedes the market as evidenced by the sharp increase in the quality difference. Duopoly innovation is higher than monopoly innovation when substitutability is near the shakeout threshold.

Summary of results. The rate of innovation in product quality would be 4.2%

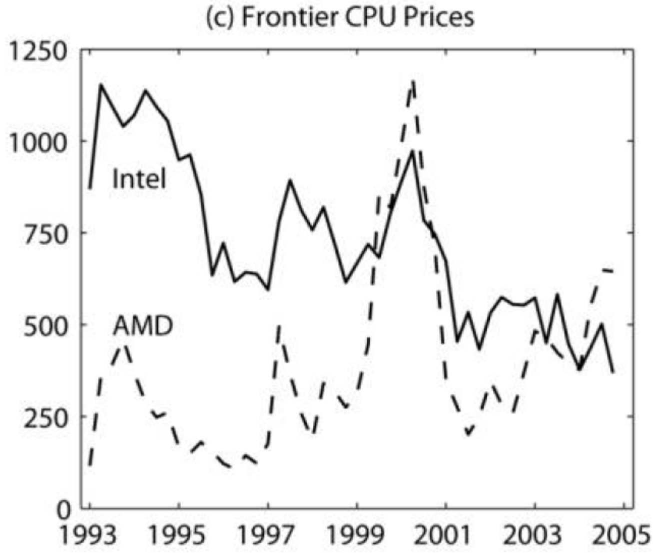

Figure 9.20: Frontier CPU Prices

higher if Intel were a monopolist, consistent with Schumpeter.

Without AMD, higher margins spur Intel to innovate faster to generate upgrade sales. As in **coase_1972**'s (**coase_1972**) conjecture, product durability can limit welfare losses from market power. This result, however, depends on the degree of competition from past sales. If first-time purchasers were to arrive sufficiently faster than we observe, innovation in an Intel monopoly would be lower, not higher, since upgrade sales would be less important.

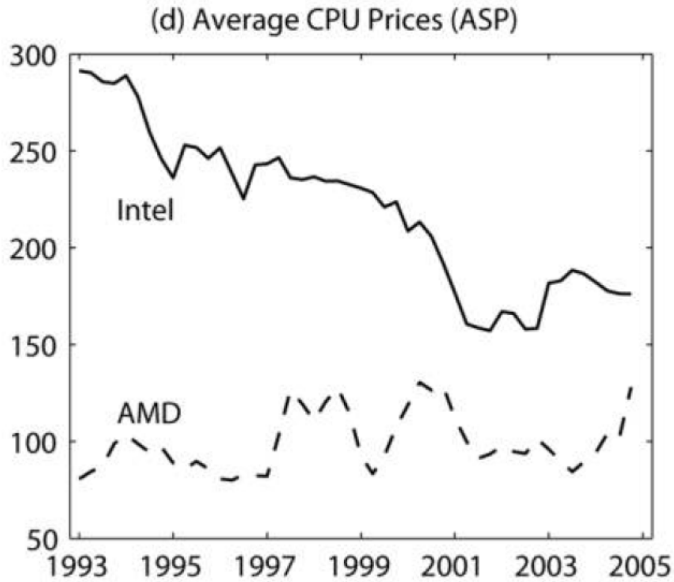

Figure 9.21: Average CPU Prices

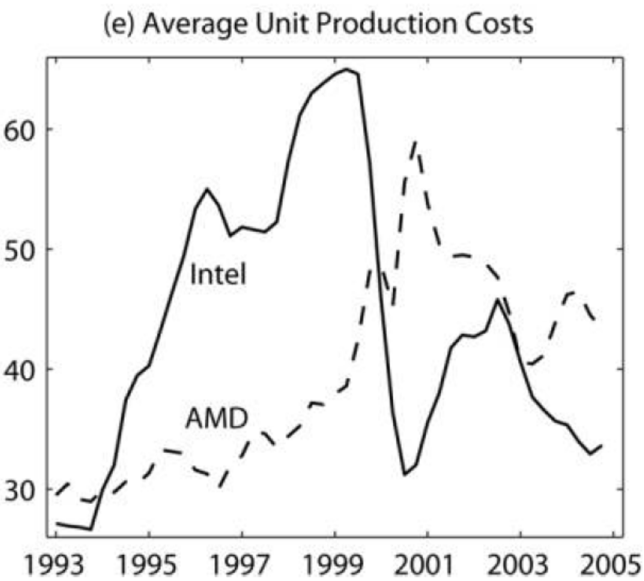

Figure 9.22: Average Unit Production Costs

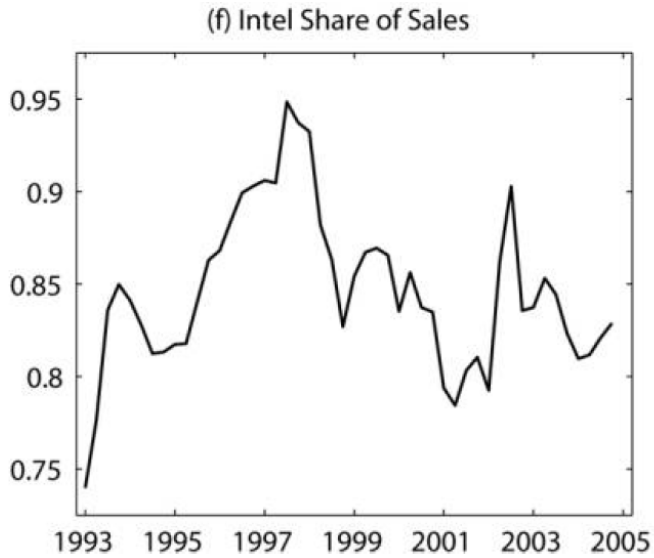

Figure 9.23: Intel Share of Sales

TABLE 1
EMPIRICAL AND SIMULATED MOMENTS

Moment	Actual	Actual Standard Error	Fitted
Intel price equation:			
Average Intel price	219.7	5.9	206.2
$q_{\text{Intel},t} - q_{\text{AMD},t}$	47.4	17.6	27.3
$q_{\text{Intel},t} - \bar{\Delta}_t$	94.4	31.6	43.0
AMD price equation:			
Average AMD price	100.4	2.3	122.9
$q_{\text{Intel},t} - q_{\text{AMD},t}$	−8.7	11.5	−22.3
$q_{\text{AMD},t} - \bar{\Delta}_t$	16.6	15.4	5.9
Intel share equation:			
Constant	.834	.007	.846
$q_{\text{Intel},t} - q_{\text{AMD},t}$	.055	.013	.092
Potential upgrade gains:			
Mean $(\bar{q}_t - \hat{\Delta}_t)$	1.146	.056	1.100
Mean innovation rates:			
Intel	.557	.047	.597
AMD	.610	.079	.602
Relative qualities:			
Mean $q_{\text{Intel},t} - q_{\text{AMD},t}$	1.257	.239	1.352
Mean $\mathcal{I}(q_{\text{Intel},t} \geq q_{\text{AMD},t})$	.833	.054	.929
Mean R&D/revenue:			
Intel	.114	.004	.101
AMD	.203	.009	.223

Figure 9.24: Empirical and predicted moments

TABLE 2
PARAMETER ESTIMATES

Parameter	Estimate	Standard Error
Price, α	.0131	.0017
Quality, γ	.2764	.0298
Intel fixed effect, ξ_{Intel}	$-.6281$	.0231
AMD fixed effect, ξ_{AMD}	-3.1700	.0790
Intel innovation, $a_{0,\text{Intel}}$	.0010	.0002
AMD innovation, $a_{0,\text{AMD}}$	.0019	.0002
Spillover, a_1	3.9373	.1453
Stage 1 marginal cost equation:		
Constant, λ_0	44.5133	1.1113
max $(0, q_{\text{competitor},t} - q_{\text{own},t})$, λ_1	-19.6669	4.1591

Figure 9.25: Parameter Estimates

TABLE 3
Industry Outcomes under Various Scenarios

	AMD-Intel Duopoly (1)	Symmetric Duopoly (2)	Monopoly (3)	No Spillover Duopoly (4)	Myopic Pricing: AMD-Intel (5)	Myopic Pricing: Monopoly (6)
Industry profits ($ billions)	408	400	567	382	318	322
Consumer surplus (CS)	2,978	3,012	2,857	3,068	2,800	2,762
CS as share of monopoly CS	1.042	1.054	1.000	1.074	.980	.967
Social surplus (SS)	3,386	3,412	3,424	3,450	3,118	3,084
SS as share of planner SS	.929	.906	.940	.916	.828	.819
Margins, $(p - mc)/mc$	3.434	2.424	5.672	3.478	2.176	2.216
Price	194.17	146.73	296.98	157.63	140.06	143.16
Frontier innovation rate	.599	.501	.624	.438	.447	.438
Industry investment ($ millions)	830	652	1,672	486	456	787
Mean quality upgrade (%)	261	148	410	187	175	181
Intel or leader share	.164	.135	.143	.160	.203	.211
AMD or laggard share	.024	.125		.091	.016	

Figure 9.26: Counterfactuals

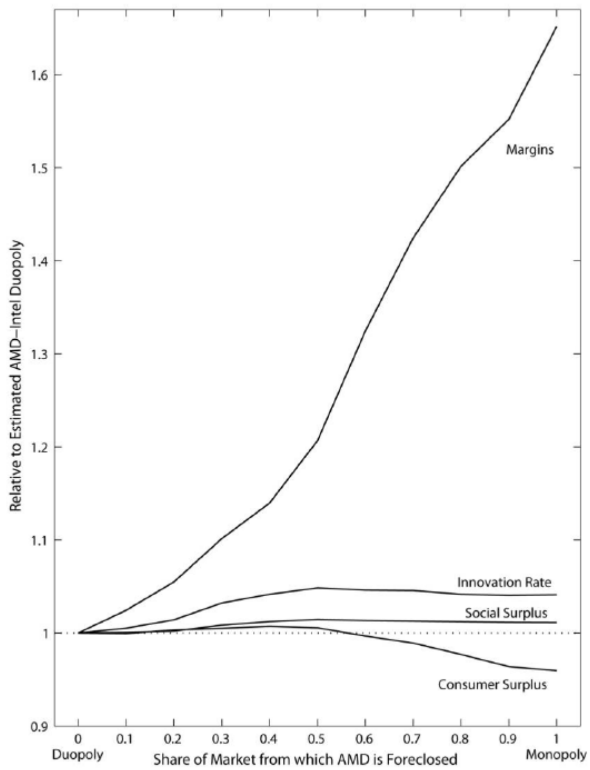

FIG. 6.—Foreclosing AMD from the market

Figure 9.27: Counterfactuals: Foreclosure

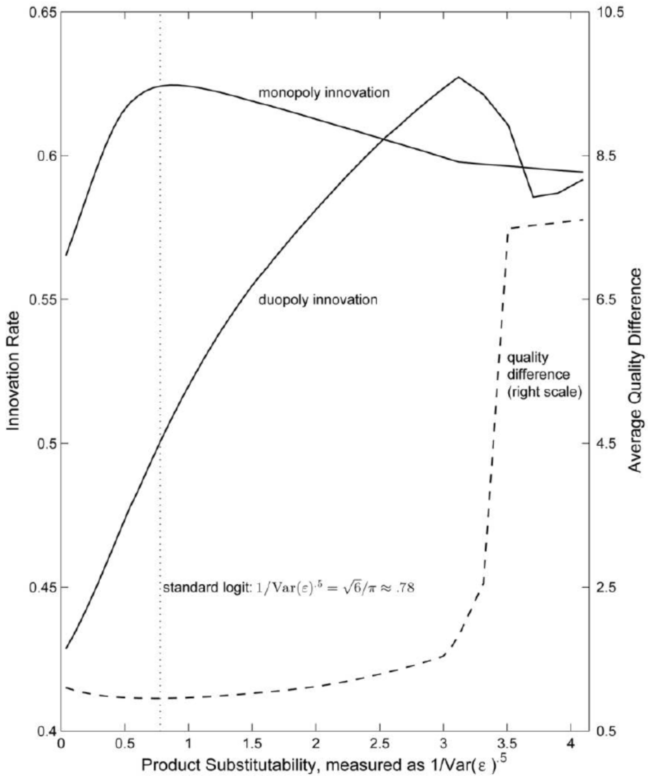

Figure 9.28: Counterfactuals: Product substitutability