THE RELATIONSHIP BETWEEN MARKET STRUCTURE AND INNOVATION IN INDUSTRY EQUILIBRIUM: A CASE STUDY OF THE GLOBAL AUTOMOBILE INDUSTRY

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Abstract—We specify and estimate a dynamic game to study the equilibrium relationship between market structure and innovation in the automobile industry. The quality of each firm's product for the average consumer, the key state variable, is modeled as stochastically increasing in innovation, the dynamic control, which is proxied by patent applications. Equilibrium innovation is a function of market structure, the vector of quality levels of all active firms, and the cost of R&D. Our main findings are as follows: (a) optimal innovation has an inverted-U shape in own quality; (b) holding own quality constant, innovation is declining in average rival quality but increasing in quality dispersion; and (c) following entry, each incumbent's innovation declines, but aggregate innovation increases in most market structures. These findings are broadly consistent with the Schumpeterian hypothesis that market power leads to more innovation.

I. Introduction

SCHUMPETER (1942) advanced the controversial argument that monopoly is more conducive to innovation than highly competitive markets. This motivated an extensive empirical literature.[1] Most studies employ reduced-form econometric techniques and regress some measure of innovation on a measure of market structure, but the literature has not produced conclusive findings. One explanation is that the theoretical relationship is monotonic only under restrictive circumstances (Boone, 2000; Gilbert, 2006). In particular, Vives (2008) showed that otherwise robust patterns are still sensitive to an assumption of endogenous versus exogenous market structure. Even when within-industry variation is exploited, as in Blundell, Griffith, and Van Reenen (1999), unobserved firm heterogeneity complicates identification.

The most rigorous applications use instrumental variables to deal with the possible endogeneity of market structure.[2] In contrast, we study this classic question using a fully specified structural model. It has the advantage of explicitly incorporating the evolution of market structure. Within the confines of the model, we can study the impact of an exogenous change in market structure on optimal innovation, while still allowing reverse effects of current innovation on the future market structure. A second advantage is the possibility of running counterfactual experiments. We look in particular at the impact of entry on innovation. A related advantage is the possibility to consider market structures that are not observed in the limited time frame of the data. The equilibrium of our model includes an optimal innovation strategy for each firm in every possible market structure. We can then compare firms' behavior when they face different states of the industry, that is, different competitive situations, holding everything else constant.

The structural approach, though attractive, has its own problems. Most important, one needs to make several functional form and other simplifying assumptions to make the estimation of the model and computation of equilibrium feasible. To limit these concerns, we have adopted demand and marginal cost specifications and behavioral assumptions that are commonly used in empirical work. We also perform a few robustness tests to verify the sensitivity of our estimates. Our results indicate that in spite of the necessary simplifications, the model still leads to an innovation policy that is quite sensitive to the market structure.

Our approach can be thought of as a theory-guided exercise to measure market structure and innovation and study the equilibrium relationship between them. The estimated structural model rationalizes the observed behavior in the data. We then use it to understand the intricate ways in which innovation incentives are shaped by different aspects of competition and to study innovation incentives in situations that are not observed.

In our model, each firm produces a differentiated product that is characterized by the firm's product quality. As consumers trade off price and quality, a firm has two levers to influence its market share and profits: price and investment in R&D. The price affects only the current profits and has no impact on future decisions. It is chosen strategically in each period, taking qualities of rival products as given. The investments in R&D, however, can have long-lasting effects as they stochastically increase the quality of a firm's product. This is a strategic and forward-looking decision that requires a dynamic model as costs and benefits accrue in different periods. The optimal R&D policy of a firm takes the actions of its rivals into account, as well as its impact on the likelihood of possible future market structures.

We estimate our model on the global automobile industry, which provides an interesting environment to study the relationship between market structure and innovation. It is one of the most innovative industries in terms of both R&D expenditure and patents granted. Many firms in the industry have experienced a pronounced change in their competitive position over the sample period, 1982 to 2006, which provides identifying power to estimate the structural

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[1] Cohen and Levin (1989), Gilbert (2006), and Cohen (2010) survey this literature.

[2] Carlin, Schaffer, and Seabright (2004), Aghion et al. (2005), and Hashmi (2013) are recent examples.

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parameters. The more globalized operations of some initially regional firms have made the global market structure more symmetric, with a diminished role for fringe firms and for the very largest firms.

Only a few other papers have studied the interrelation between innovation and market structure in a dynamic model of strategic interaction. Goettler and Gordon (2011) study the microprocessor industry and explicitly incorporate the durable nature of the good by making demand and price-setting dynamic as well. They estimate the primitives from the actual AMD-Intel duopoly and perform a counterfactual analysis of innovation under monopoly. They find that Intel would innovate more as a monopoly, but this depends crucially on the durable nature of the good. Product upgrades are necessary to stimulate demand, and they happen only if consumers value quality highly and are relatively price insensitive.

Xu (2008) analyzes innovation decisions in the Korean electric motor industry. In addition to the cost of R&D, he also estimates R&D spillovers, adjustment costs of physical investment, and the distribution of plant scrap value. As he uses the oblivious equilibrium concept of Weintraub, Benkard, and Roy (2008), there is no strategic interaction between plants in the innovation decision. Plants only optimize relative to a stable industry state. Finally, Siebert and Zulehner (2010) study the reverse question of ours: how does innovation affect market structure? In their study of the dynamic random-access memory industry, they estimate the evolution of sunk entry costs as the innovation intensity and market demand increase over time. Through their effects on entry and exit, these costs determine equilibrium market structure.

Our approach differs from these other studies in a number of ways. First, we model a continuous control variable, innovation rather than a 0-1 decision in the more common discrete dynamic games. We rely on the two-step estimation strategy of Bajari, Benkard, and Levin (2007), which does not require solving for the equilibrium. This estimator has been used in only a few other empirical applications.[3]

Second, we estimate a model of dynamic industry equilibrium for the automobile industry, a popular proving ground for static models of firm competition in industrial organization. Hence, we can rely on functional form and behavioral assumptions that are widely used and well understood. Our approach differs from Goettler and Gordon (2014), who study how innovation incentives and optimal policies change as they vary the parameter values for key primitives. We use only the policy vector calculated from the estimated parameter values and the most plausible behavioral assumptions for the industry we study. Even in this limited setting, we find innovation incentives to vary greatly with the competitive situation a firm faces.

Third, we study the impact of market structure on innovation by comparing the equilibrium innovation policies at different values for the industry state. Within the confines of the model, this can be interpreted as a causal effect. Exogenous shocks, such as entry, mergers, or even a lucky series of quality improvements, can easily lead to industry states that differ from any we observe in the data, but this does not pose any problem. Our approach differs from Benkard, Bodoh-Creed, and Lazarev (2010), who use only the policies that are estimated directly from the observable data. While they do not need to solve for the equilibrium, they need to assume that firms have no overall design for their network such that data from different markets provide independent information.[4]

A key finding is that market structure has a nuanced effect on innovation incentives which makes it difficult to summarize overall patterns. A few facts stand out. First, optimal innovation has an inverted-U shape in own quality. Because in our model the price-cost markup tends to be increasing in own quality, this pattern mimics the relationship first illustrated in Aghion et al. (2005), though in our case, it is at the firm level and not at the industry level. While opposing efficiency and replacement effects are also at play in our model, technological features of the estimated cost and quality improvement functions are very important as well. Second, holding own quality and all primitives constant (e.g., substitutability of products, cost and effectiveness of R&D, impact of quality on marginal cost), optimal innovation is quite sensitive to the competitive situation a firm faces. Specifically, it is decreasing in average rival quality and increasing in quality dispersion. Third, following entry, innovation by incumbents unambiguously declines. These last findings are consistent with the Schumpeterian hypothesis, but not with several recent studies that find stronger international competition to boost innovation.[5] However, we do find that aggregate innovation increases following entry in most states of the industry.

The rest of the paper is organized as follows. In section II, we provide background information on the global automotive industry and the data we use. In section III, we introduce the static and dynamic elements of the model as well as the Markov Perfect Equilibrium concept. We present the two-step estimation methodology and the parameter estimates in section IV. In section V, we use the estimated model to analyze the equilibrium interaction between innovation and market structure. We conclude in section VI.

II. Background on the Industry and Data

A. *Innovation*

The automotive industry is well suited to investigate the interaction between innovation and market structure in a

[3] Two examples are Ryan (2012), who studies the effect of environmental regulation on the cement industry, and Ching (2010), who modified the estimator to simultaneously estimate the demand and policy functions and study demand dynamics for prescription drugs after patent expiry.

[4] Saying anything about states that are not observed in their approach requires purely statistical extrapolation.

[5] See Bloom, Draca, and Van Reenan (2011) or Aw, Roberts, and Xu (2011), among others.

TABLE 1.—R&D EXPENDITURE BY INDUSTRY IN SELECTED COUNTRIES, 2006 (IN PPP $BILLION)

Industry (ISIC Rev. 3)	United States	Japan	Germany	Korea	France
Chemicals (24)	46.3	16.4	8.2	2.1	5.0
Radio, TV, Telecommunications Equipment (32)	31.2	12.2	4.1	13.3	2.8
Motor Vehicles (34)	16.6	17.9	14.4	4.2	4.6
Medical, Precision, Optical Instruments (33)	22.4	4.6	3.5	0.4	1.6
Computing and Related Machinery (30)	7.4	14.1	0.6	0.4	0.2

Includes all sectors in the top three by R&D expenditure in any of the five countries. Industries are sorted by total R&D expenditure across the five countries.
Source: OECD ANBERD database, edition 2009 (online).

strategic context. Demand estimates (see, e.g., Berry, Levinsohn, & Pakes, 1995, and Goldberg, 1995) indicate large markups over marginal costs, consistent with the view that fixed costs are important in this industry. Innovation is an important source of product differentiation as firms improve their competitive position through higher product quality, greater reliability, and the introduction of new product features. In addition, the industry is the poster child for the importance of productivity-enhancing process innovations (Van Biesebroeck, 2003).

Producing automobiles is a highly research-intensive activity. In 2003, more than 13% of all R&D in OECD countries was by firms in ISIC industry 34, Motor Vehicles, more than in any other industry. In 2006, the industry was in third place. Statistics in table 1 illustrate the importance of automotive R&D in the five most innovative economies. The industry is in first or second place in terms of R&D spending in each country, except for the United States, where it is fourth. The top thirteen automotive firms spent more than $55 billion on R&D in 2005, and the share of automotive research that is publicly funded is smaller than the economy-wide average.

The industry is also a heavyweight on the output side of the innovation process. In the 25-year sample period, these same thirteen firms were awarded more than 50,000 patents by the U.S. patent office.[6] In the estimation, we use the annual number of patents a firm applies for as a proxy for its innovative activities.[7] We use patents applied for rather than patents granted to minimize time delay problems. We use patents rather than R&D expenditures because the R&D data have only become available in recent years through consolidated global accounts, and those too are not available for all firms. Moreover, these firms spend large amounts on engineering and product design, which in some countries might be partially included in R&D expenditures.

The information on patenting comes from the PATSTAT database. Since firms often file for patents through various subsidiaries, we searched the database for all records containing the core of the parent firm's name and manually verified the results. The number of applications for each firm-year observation to the U.S. and European patent offices are combined as follows: $x_{jt} = \max(x_{jt}^{US}, \lambda x_{jt}^{EU})$. λ is the relative weight given to more expensive and more demanding European patents. It is computed by taking the ratio of U.S. to European patent applications of four large firms that have significant sales and production in both regions: Daimler, Ford, Honda, and Toyota. We compute this weight to be 2.36. Our interpretation is that for automotive firms, one European patent represents the same amount of innovation as 2.36 American patents.

TABLE 2.—MARKET SHARES IN THE INITIAL AND FINAL YEAR OF THE SAMPLE

	1982		2006	
	Sales (000)	Market Share	Sales (000)	Market Share
GM	6,463	17.3%	8,680	12.5%
Ford	5,415	14.5%	7,242	10.4%
Toyota	3,282	8.8%	8,808	12.7%
Nissan	2,604	7.0%	3,478	5.0%
VW	2,200	5.9%	5,720	8.2%
Renault	2,026	5.4%	2,433	3.5%
Fiat	1,798	4.8%	2,288	3.3%
PSA	1,644	4.4%	3,366	4.8%
Chrysler	1,408	3.8%	[merged with Daimler]	
Honda	1,015	2.7%	3,550	5.1%
Daimler	701	1.9%	4,749	6.8%
Suzuki	606	1.6%	2,174	3.1%
BMW	377	1.0%	1,374	2.0%
Hyundai	91	0.2%	3,753	5.4%
Sample total	29,631	79.4%	57,615	83.0%
Global total	37,337		69,438	

Source: *Ward's Automotive and Automotive News*.

B. *Market Structure*

The automotive industry is concentrated globally, making it likely that firms will take actions of competitors into account when deciding on their own level of innovation. We measure sales by the number of vehicles sold worldwide by each firm and its affiliates. This information is obtained from Ward's Info Bank, the Ward's Automotive Yearbooks, and the online data center of Automotive News for the most recent years. Market shares in table 2 are computed as a fraction of total worldwide new vehicle sales.

We focus on only the largest firms as we are primarily interested in strategic interactions. Using as the inclusion criterion "at least 1% of global sales in any year," we are left with a sample of fourteen firms. The merger between Daimler and Chrysler in 1998 is treated as an exogenous

[6] Five percent of all patents filed in the European patent office (by EU applicants) are in the narrow IPC category B60 Vehicles in General, which is only 1 of 127 categories and contains only a subset of motor vehicle–related innovations. The corresponding fraction at the U.S. patent office is 3%.

[7] Patents are a widely used measure of innovation output. In a survey on the use of patents as a measure of technological progress, Griliches (1990) concludes, "In spite of all the difficulties, patents statistics remain a unique resource for the analysis of the process of technical change" (p. 1701).

event that reduced the number of firms to thirteen.[8] Together these firms sold 79% of all new vehicles worldwide in 1982 and 83% in 2006. They almost surely account for an even larger fraction of innovation.[9] The balance of new vehicle sales is by smaller firms, and we assume that they do not innovate strategically. In the model, their sales are captured by an outside good.

A few important changes in market structure between 1982 and 2006 stand out in table 2. As the largest firms—GM, Ford, and the union of Nissan-Renault—lost market share and the smallest firms gained the most, the industry became more symmetric. While many firms still made the bulk of their sales in their home region in 1982, by 2006 all firms operated globally. The sample firms also took market share away from the peripheral firms, partly as a result of takeovers. The fortunes of the firms that gained market share also varied tremendously. While PSA increased its share by one-tenth, from 4.4% to 4.8%, Honda almost doubled it, from 2.7% to 5.1%, and Hyundai increased it by a factor of more than 20, from 0.24% to 5.4%.

C. *Other Variables*

It would be infeasible to model firms as planning the full evolution of their product portfolio in a strategic and forward-looking manner. In the dynamic model, we abstract from the different vehicle models each firm sold. Instead, we assume a single model that is characterized by a price and a quality level. The trade-off between these two characteristics is captured by the demand curve. It is estimated jointly with the marginal cost curve using the full set of models and taking more detailed vehicle characteristics into account, as in Berry et al. (1995).

We have updated the data sets for the U.S. new vehicle market from Petrin (2002) and the new vehicle market in five European countries from Goldberg and Verboven (2001) to 2006 using comparable information from JATO Dynamics. The product characteristics we use are size (length × width × height), horsepower by weight, and fuel efficiency (miles per dollar). We use list prices for the base models.

For the dynamic estimation, we construct a firm-level average price within each region as the sales-weighted average of the prices of individual models. Prices are deflated using the CPI for New Vehicles from the U.S. Department of Labor and using the Harmonized Index of Consumer prices for Motor Cars in the euro area from Eurostat (1996–2006) or the respective European countries' CPI (prior to 1996). To aggregate across the two regions, we first deflate prices within each region and then divide the European prices by 1.25. This was the average euro–dollar exchange rate in 2006 and similar to the 1.21 average rate for 1994, the midpoint of the sample.[10]

Table 3.—Summary Statistics

Variable	Mean	SD	10th Percentile	90th Percentile
Patent applications	255	255	11	607
Sales (in thousands)	3,177	2,362	748	7,626
Price (in thousands of 1983 $)	11.3	4.08	7.24	18.2

The number of observations for each variable is 341.

Summary statistics for the three variables used in the dynamic model are reported in table 3. The fourth variable, firm quality, will be constructed from the estimated demand function. Recall that the sample contains thirteen to fourteen firms over 25 years (1982–2006). The included firms are highly innovative, applying for an average of 255 patents per year, but the variation in innovative activities is quite large. Average annual sales is 3.2 million vehicles, and the average vehicle sells for $11,300 in 1983 U.S. dollars.

D. *A First Look at the Relationship*

To illustrate the difficulty of learning about the nature of the relationship between competition and innovation, we plot in figure 1 the empirical relationship in the raw data. In the top panel we use market-level information, the average across active firms of the number of patent applications per million dollars of revenue versus the Herfindahl index (HHI) of the firms' market shares.

Overall, it seems that lower concentration or more competition is associated with higher innovation. The pattern is weak, but the negative coefficient on the linear HHI term in the fitted (cubic) line is highly significant. This pattern relies solely on time series variation. As concentration has fallen over time, patenting has risen. Whether this relationship is causal is difficult to say. It is well known, for example, that the overall rate of patenting in the economy has increased over time, especially since 1984 (Hall, 2004).

Concentration in market share is, of course, only one possible measure of competition. In Hashmi and Van Biesebroeck (2012), we used a broader sample of firms, and over the same time period, industry consolidation reduced the number of independent firms gradually from 24 to 13. Given that average innovation (as well as aggregate innovation) was also increasing over time, that pattern would suggest a reverse interpretation. Fewer firms (i.e., less competition) are conducive to innovation.

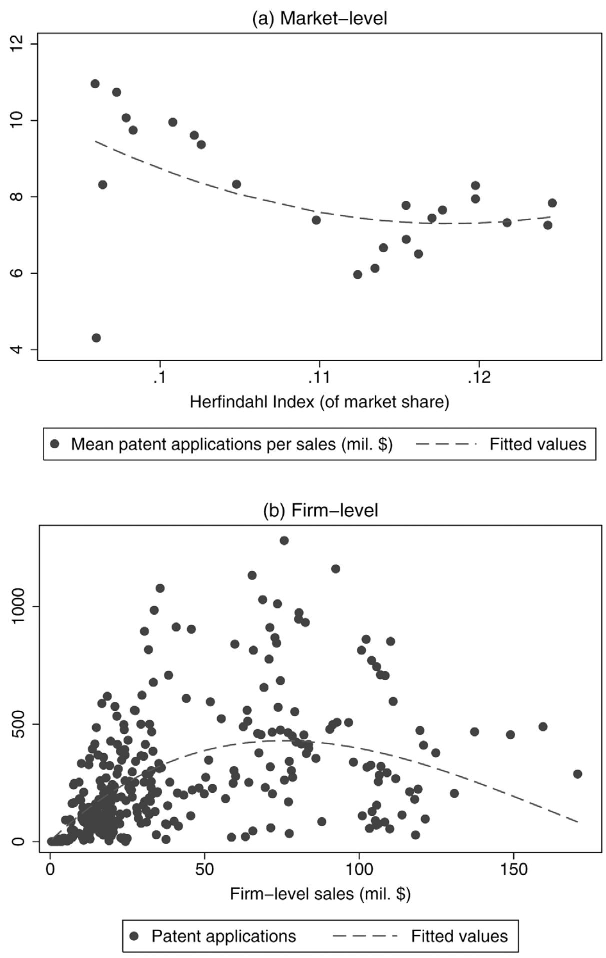
The aggregate relationship hides important underlying variation. Even conditioning on the extent of competition in the industry in a given year, innovation differs widely across firms. The relationship between firm size, measured by real revenue, and the number of patent applications is depicted

[8] We also estimated the model treating the partnership between Nissan and Renault in 1999 as a merger, but this had little impact on the estimates.

[9] Based on patent applications from automotive firms headquartered in the United States, Europe, Japan, or South Korea, the fraction exceeds 95%.

[10] At the start of the sample period, the exchange rate fluctuated a lot, with the weighted national currency equivalent of the euro–dollar exchange rate declining from 1.35 in 1980 to 0.74 in 1985 and recovering subsequently to 1.30 in 1992.

FIGURE 1.—EMPIRICAL RELATIONSHIP BETWEEN INNOVATION AND MARKET STRUCTURE



in the bottom panel of figure 1 (pooling all years). The fitted line is estimated using year fixed effects that absorb anything year specific but constant across firms, such as the increasing rate of patenting. The relationship is inverted-U shaped.[11] The smallest firms tend to patent the least, while the most innovative firms are those in the middle of the size distribution.

This pattern is consistent with the evidence for U.K. manufacturing firms in Aghion et al. (2005). Even the earlier patterns at the industry level—higher innovation with lower concentration or with fewer competitors—could be consistent with opposing efficiency and replacement effects, but with different effects dominating depending on the market structure proxy. To gauge whether the mechanisms that generate these patterns in the automobile industry are consistent with the interpretation in Aghion et al. (2005), we need a model of firm behavior and industry competition.

[11] In Hashmi and Van Biesebroeck (2012), we show graphs for individual years and the same inverted-U relationship appears. The pattern is even more pronounced using patents by revenue as the innovation measure.

III. The Model

We write a simple model of industry equilibrium with forward-looking innovation decisions. Firms decide on their innovation effort based on the current market structure and a (private) cost of innovation. At the same time, they realize that their individual decisions collectively and stochastically determine the evolution of the market structure. Our modeling strategy follows Ericson and Pakes (1995) except for the absence of entry and exit, which have not been important in this industry over the last decades.

To study strategic innovation decisions, our unit of analysis is the firm. However, to obtain credible estimates of the demand and marginal cost parameters, we start at a more disaggregated level. We first specify the static, within-period problem as that of a multiproduct oligopolist choosing prices for all its products while taking all quality levels and the prices of its rivals as given. This leads to a demand equation and first-order condition for optimal price setting that can be estimated jointly. We then show how these two equations can be aggregated to the firm level. There is no rigorous foundation for the aggregation to a firm-level demand equation, but it is necessary to make tractable the estimation and analysis of the dynamic model.[12]

In the dynamic problem, time is discrete. Firms are heterogenous with respect to their relative quality level, the state variable ξ_j, which combines both observable and unobservable features that make a firm's product attractive to consumers. At the beginning of each period, firms observe the full state vector for the industry, their own cost of innovation, and they decide on price and investment in R&D. While price setting can be thought of as the equilibrium outcome of a static Bertrand-Nash game, the investment decisions are the outcome of a dynamic game of incomplete information. We now provide some details of both static and dynamic decisions.

A. *The Static Problem*

The demand system is derived from a discrete choice model of individual consumer behavior, following Berry et al. (1995) and many others studying the automobile industry. There are n active firms, and firm j produces K_j different vehicle models. There are m consumers in the market, and each buys one vehicle. The utility that consumer i derives from buying vehicle k_j depends on a vector of vehicle characteristics X_{k_j}, a dimension of quality differentiation $\tilde{\xi}_{k_j}$ that is unobservable to the econometrician, the price, and an additive and idiosyncratic preference shock:[13]

$$u_{ik_j} = X'_{k_j}\beta + \theta_p p_{k_j} + \tilde{\xi}_{k_j} + \varepsilon_{ik_j}. \quad (1)$$

[12] Moreover, different ways to define the firm-level price (we used a quantity-weighted average) will lead to minor differences in firm-level relative qualities.

[13] We do not use a random coefficients model because our focus is on the effect of innovation at the firm level, which does not require detailed substitution patterns.

Assuming that the idiosyncratic utility shock ε_{ik_j} is i.i.d. extreme value distributed, we obtain the following expected market share for model k_j:

$$\sigma_{k_j} = \frac{\exp(X'_{k_j}\beta + \theta_p p_{k_j} + \tilde{\xi}_{k_j})}{1 + \sum_{l=1}^{n}\sum_{k_l}\exp(X'_{k_l}\beta + \theta_p p_{k_l} + \tilde{\xi}_{k_l})}. \quad (2)$$

The expected demand for model k_j is $m\sigma_{k_j}$.

A number of smaller firms do not innovate strategically. We combine them into a single benchmark firm and normalize for one of its models the sum of observed and unobserved vehicle quality to 0: $\xi_{k_0} \equiv X'_{k_0}\beta + \tilde{\xi}_{k_0} = 0$.[14] Taking logs and normalizing, we obtain the following estimating equation for demand at the model level:

$$\ln \sigma_{k_j} - \ln \sigma_{k_0} = X'_{k_j}\beta + \theta_p(p_{k_j} - p_{k_0}) + \tilde{\xi}_{k_j}. \quad (3)$$

On the supply side, we assume a Nash equilibrium in strategic price setting for differentiated goods. Firms take into account the cross-price effects on the demand for all their products, while taking the industry state as given. Firm j's own state is a vector $\bar{\xi}_j = [\xi_1\ \xi_2\ \cdots\ \xi_{K_j}]$, where $\xi_{k_j} = X'_{k_j}\beta + \tilde{\xi}_{k_j}$ combines all product characteristics that consumers value. The profit maximization problem of firm j is

$$\pi_j(\bar{\xi}_j, \bar{\xi}_{-j}, \mathbf{p}_{-j}, m|\theta_p, \theta_c) = \max_{\mathbf{p}_j} \sum_{k_j=1}^{K_j}\{p_{k_j} - \mu_{k_j}(\xi_{k_j}|\theta_c)\}\, m\sigma_{k_j}(p_{k_j}, p_{-k_j}, \mathbf{p}_{-j}|\theta_p).$$

μ_{k_j} is the marginal cost of producing model k_j and is allowed to vary with quality. Following Berry et al. (1995), we specify marginal cost as a log linear function,

$$\ln \mu_{k_j} = \theta_{c1} + \theta_{c2}\xi_{k_j} + \zeta_{k_j}. \quad (4)$$

This includes an unobservable (to the econometrician) shock ζ_j, which is assumed to be i.i.d. across firms and over time with mean 0. Higher vehicle quality could translate into higher costs, but cost-reducing process or design innovations could lower production costs while making products more reliable and attractive.

Given the logit demand specification, the first-order condition for model k_j simplifies to

$$p_{k_j} = \exp(\theta_{c1} + \theta_{c2}\xi_{k_j} + \zeta_{k_j}) - \frac{1}{\theta_p\left(1 - \sum_{k_j=1}^{K_j}\sigma_{k_j}\right)}. \quad (5)$$

We have to solve $\sum_j K_j$ such first-order conditions simultaneously to obtain the equilibrium price vector.[15] The price of each model equals the sum of its marginal cost and a markup term. The markup is the same for all models produced by one firm but differs for firms with different aggregate market share. The demand and pricing equations (3) and (5) will be estimated simultaneously. As a robustness check, we also estimate the demand equation alone and assume constant marginal costs.

[14] This normalization plays a role similar to the outside good in other applications, only there the full utility from buying the outside good (which includes the price) is normalized to 0.

[15] The existence and uniqueness of equilibrium in this context are proved by Caplin and Nalebuff (1991).

B. Aggregation to the Firm Level

The above model is fairly standard in the empirical IO literature. From utility-maximizing consumer choices and (static) profit-maximizing price setting, it generates estimates for the two key primitives we need from the static model: the price sensitivity of consumers and the impact of quality on marginal production costs. Innovation, however, is a firm-level decision regarding a global R&D budget. Innovations have the potential to boost the quality of all the firm's models.

The random utility function can also be specified directly at the firm level. The utility that consumer i obtains from purchasing the representative product of firm j is

$$u_{ij} = \theta_p p_j + \xi_j + \varepsilon_{ij}. \quad (6)$$

Here we lump the observable and unobservable product characteristics in a single quality index ξ_j, but the price coefficient has the exact same interpretation as in equation (1).

The same extreme value assumption and normalization as before now generates an expression for the relative product quality:

$$\xi_j = (\ln \sigma_j - \ln \sigma_0) - \theta_p(p_j - p_0). \quad (7)$$

This implicit definition of quality as the residual of the demand equation—the firm's (relative) market share adjusted by its (relative) price—mirrors the approach in Khandelwal (2010). Market shares are determined by price, which is chosen in the short run, and quality, which is fixed in most models. In our case, quality is a state variable under the firm's control, but it evolves only slowly as the benefits of innovation accumulate. Similar to Ackerberg, Crawford, and Hahn (2011), we only need the parameter governing the price elasticity and lump other determinants of market share into the quality term.

The first-order condition for price setting is entirely unchanged. We already saw that the optimal markup for a multiproduct firm facing a logit demand depends on only its aggregate market share. Assuming that the sensitivity of marginal cost with quality at the model level also holds at the firm level, we can express the supply-side equation in relative terms as

$$p_j - p_0 = \exp(\theta_{c2}\xi_j + \zeta_j - \zeta_0) - \frac{1}{\theta_p}\left(\frac{1}{(1-\sigma_j)} - \frac{1}{(1-\sigma_0)}\right). \quad (8)$$

If a firm's quality relative to that of a peripheral firm cannot grow infinitely large, the dynamic problem is naturally bounded.[16]

The aggregate price of firm j is the sales-weighted average of the prices of its K_j models. Equation (7) then provides the quality levels for firms in the observed industry states. Together with a full set of first-order conditions, equation (8), and an evolution of the peripheral firm's marginal cost, it allows us to calculate relative prices and market shares from each industry state (vector of firm qualities). Once the parameter values for θ_p and θ_c are known, the vector of equilibrium profit values for all firms can also be calculated for any state of the industry using[17]

$$\pi_j^*(\xi_j, \xi_{-j}, m|\theta_p, \theta_c) = \{p_j^* - \mu_j(\xi_j|\theta_c)\}\, m\sigma_j(\xi_j, \xi_{-j}, p_j^*, p_{-j}^*|\theta_p). \tag{9}$$

C. The Dynamic Problem

Firms innovate because innovation has the potential to increase the quality of their products. To analyze this decision, we first have to be more specific about the domain of ξ. Ξ is defined by specifying lower and upper bounds and discretizing the intermediate range of possible values in steps of Δ_ξ. As a result, $\Xi = \{\xi_{\min}, \xi_{\min} + \Delta_\xi, \ldots, \xi_{\max} - \Delta_\xi, \xi_{\max}\}$. Recall that ξ_j is the relative quality of firm j, normalized by the quality level of a peripheral firm. This makes it likely that ξ_j is naturally bounded.

The cost of R&D comprises a common part and a private shock ν_j. The first is allowed to vary with R&D expenditure x_j, and the second is assumed i.i.d. across firms and observed only by firm j. The random shocks have a similar interpretation as the choice-specific state variables in Rust (1987) or Gowrisankaran et al. (2010). They ensure that each investment choice has positive probability. The state vector for firm j is $\{\xi_1, \cdots, \xi_j, \cdots, \xi_n, \nu_j\}$, which we write as $\mathbf{s}_j = \{\xi_j, \xi_{-j}, \nu_j\}$.[18] In our model, firm heterogeneity is captured by $\mathbf{s}_j$, and beyond it the firms are homogeneous.

Investment in R&D is decided strategically based on the current cost and the expected value of a future profit stream. The dynamic problem is recursive, and, assuming stationarity, it can be described by the following Bellman equation

$$V_j(\xi_j, \xi_{-j}, \nu_j|\boldsymbol{\theta}) = \max_{x_j \in \mathbb{R}^+} \Big\{ \pi_j(\xi_j, \xi_{-j}|\theta_p, \theta_c) - c\left(x_j, \nu_j|\theta_x\right) + \beta E\big[V_j(\xi_j', \xi_{-j}', \nu_j'|\xi_j, \xi_{-j}, x_j, \boldsymbol{\theta})\big]\Big\}, \tag{10}$$

where β is the discount factor and $c(\cdot)$ the cost of R&D, a function of the dynamic parameters θ_x. $\boldsymbol{\theta}$ combines all parameters of the model. The variables with a prime denote the next period values. The expectation is with respect to the evolution of the entire state vector $\mathbf{s}_j'$, and firm j conditions this on x_j, ξ_j, and ξ_{-j}, but not on ν_j which is assumed to be i.i.d. over time.

The expected value can be written explicitly as

$$\begin{aligned} &E\big[V_j(\xi_j', \xi_{-j}', \nu_j'|\xi_j, \xi_{-j}, x_j, \boldsymbol{\theta})\big] \\ &\quad = \int \sum_{\xi_{-j}'} \sum_{\xi_j'} V_j(\xi_j', \xi_{-j}', \nu_j'|\boldsymbol{\theta}) P_\xi(\xi_j'|\xi_j, x_j, \theta_t) \\ &\qquad \times P_\xi(\xi_{-j}'|\xi_{-j}, x_{-j}\left(\nu_{-j}\right), \theta_t) d\nu, \end{aligned}$$

where θ_t are the parameters in the state transition function.

The evolution of ν_j is straightforward. We assume it to be i.i.d. over time and to follow a normal distribution with 0 mean and standard deviation σ_ν, one of the dynamic parameters in the vector θ_x. We estimate the integral using Gaussian-Hermite quadrature.

The evolution of ξ_j, denoted by $P_\xi(\xi'|\xi, x, \theta_t)$, depends on the firm's innovation choice and its current product quality. Following Ericson and Pakes (1995), we assume that the next period's quality level can take only three possible values. On the discretized domain, quality can increase or decrease by one step or remain unchanged. The probability distribution over these possible future states is given by the triplet $\{p^U, p^D, p^S\}$, defined as

$$\begin{aligned} p^U &= \Pr\left(\xi_j' = \xi_j + \Delta_\xi \mid \xi_j, x_j\right), \\ p^D &= \Pr\left(\xi_j' = \xi_j - \Delta_\xi \mid \xi_j, x_j\right), \\ p^S &= 1 - p^U - p^D = \Pr\left(\xi_j' = \xi_j \mid \xi_j, x_j\right). \end{aligned} \tag{11}$$

The evolution of ξ_{-j} is governed by the same probability distribution. The only difference is that firm j does not observe its rivals' cost of R&D and needs to integrate over different possible levels of innovation x_{-j}, which themselves depend on ν_{-j}.

The solution to equation (10) is a strategy profile $x_j = \chi_j(\xi_j, \xi_{-j}, \nu_j|\chi_{-j})$. The Markov Perfect Equilibrium (MPE) of the game is a strategy profile χ_j^* that solves equation (10) given that all rivals follow the same equilibrium strategy as firm j. It is given by $\chi_j^*(\xi_j, \xi_{-j}, \nu_j|\chi_{-j}^*)$. To estimate the dynamic parameters θ_x we exploit the properties of this equilibrium strategy profile, as described in the next section.

IV. Estimation Methodology and Results

We need to estimate four sets of parameters: demand (θ_p), marginal cost (θ_c), state transitions (θ_t), and the cost of R&D (θ_x). The dynamic parameters θ_x pose the greatest challenge. With fourteen firms in the industry, the brute force method of computing the MPE and matching predicted to observed innovation decisions is computationally infeasible.

Recently a number of alternative approaches have been developed that do not require calculating the equilibrium of the game. They exploit that observed investment decisions

[16] ξ_{0t} is assumed to evolve stochastically and exogenously, and normalized to 0 in each period.

[17] We implicitly assume that the shock to marginal cost is unobserved at the time when the R&D decision is made. Hence the profits in equation (9) are expected profits.

[18] The market size m is another state variable, but we assume it is constant over time to focus on innovation incentives in a stochastic steady state.

are equilibrium outcomes and can be used directly to (nonparametrically) characterize the policy and state transition functions.[19]

We adopt the two-step estimator of Bajari et al. (2007) as it applies directly to our model with a continuous choice variable.[20] In a first step, we combine the estimated state transition probabilities and equilibrium policy function with the fully specified period profit function to obtain numerical estimates of the value function by forward simulation. In a second step, the dynamic parameters are chosen to minimize deviations from equilibrium conditions, which occur when a firm's value function is lower under the optimal policy than under a deviation.

We present the parameter estimates immediately following the discussion of the estimation methodology for the different elements of the model. To evaluate robustness, we always show two sets of results: for the benchmark model with marginal production costs that vary with quality and for the constant marginal cost case.

A. *Step 1*

Demand and cost parameters. As mentioned before, we estimate the demand and marginal cost parameters using model-level observations. Equations (3) and (5) contain two 0 mean error terms, $\tilde{\xi}_{k_j}$ and ζ_{k_j}, and are estimated simultaneously by the generalized method of moments (GMM). The usual market power shifters—vehicle characteristics of rivals—are used as instruments to control for endogeneity of price in the demand equation. These variables are also valid instruments for market share in the pricing equation.[21]

Results in table 4 are all reasonable, except for the negative sign on the fuel efficiency variable in specification (2). This could be due to the limited set of control variables we include; we can include only variables that are observed in all three data sets. Higher fuel efficiency tends to vary inversely with several other desirable characteristics of a vehicle, such as size, performance, and luxury or safety features.[22]

Demand is estimated less price sensitive when marginal cost varies with quality. The point estimate of -0.222 implies an own price elasticity of -1 for the first percentile (cheapest) model, which is just consistent with profit-maximizing price setting. At the firm level, the median elasticity is -2.06, and 95% of all elasticities lie between -4.96 and -1.26. For the constant marginal cost specification (1), all elasticities are one-third higher in absolute value.

TABLE 4.—GMM ESTIMATES FOR DEMAND AND MARGINAL COST PARAMETERS

	Constant MC (1)	Log-Linear MC (2)
Demand parameters		
Price	-0.302^{***}	-0.222^{***}
	(0.032)	(0.019)
Size	0.382^{***}	0.202^{***}
	(0.038)	(0.019)
Power/weight	0.444^{***}	0.311^{***}
	(0.064)	(0.041)
Fuel efficiency	0.082^{***}	-0.065^{***}
(miles per \$)	(0.012)	(0.014)
Marginal cost parameters		
Constant term	10.262^{***}	2.470^{***}
	(0.108)	(0.091)
Quality (ξ)		0.285^{***}
		(0.037)
Observations	6,220	6,220

***: Significant at 1%.

The second important parameter in table 4 is the positive estimate on quality in the marginal cost specification. A quality increase sufficient to boost a firm's market share by 1% will also raise its marginal production costs by 0.29%. Recall that the firm's quality includes both observable product characteristics ($X'\beta$) and a factor that only market participants observe ($\tilde{\xi}$). This effect reduces innovation incentives, all else equal.[23]

Empirical Policy Function. To calculate future profits, we also need the values of future state variables. Using the observed patent applications as the dependent variable, we characterize the empirical innovation policy as a flexible function of the full vector of state variables. Given the limited number of observations, we use the following specification:

$$\begin{aligned} x_{jt} = {} & \alpha_0 + \alpha_1 \xi_{jt} + \alpha_2 \xi_{jt}^2 + \alpha_3 \xi_{jt}^3 + \alpha_4 Rank(\xi_{jt}) \\ & + \alpha_5 Mean(\xi_{\cdot t}) + \alpha_6 SD(\xi_{\cdot t}) + \alpha_7 Skew(\xi_{\cdot t}) \\ & + \alpha_8 Kurt(\xi_{\cdot t}) + \alpha_9 IQR(\xi_{\cdot t}) + \alpha_{10} \mathrm{Max}(\xi_{\cdot t}) \\ & + e_{jt}, \end{aligned} \tag{12}$$

which includes a cubic function of the firm's own quality and several terms that summarize the quality levels observed among active firms. These include the first four moments of the quality distribution—the mean, standard deviation, skewness, and kurtosis—and aspects of the range of quality that is observed—the maximum, interquartile range, and the firm's own rank in the industry. e_{jt} is an approximation error between the innovation level that the true policy function calls for and our prediction.

A few patterns in table 5 are worth mentioning. Higher own quality leads to more innovation, but the relationship is inverted-U shaped. The negative terms are large enough to

[19] While this approach is widely used in single-agent dynamic problems since Hotz and Miller (1993), in a dynamic game context the assumption is less innocuous due to the possibility of multiple equilibria (see Doraszelski & Pakes, 2007).

[20] Alternative approaches include Aguirregabiria and Mira (2007) and Pakes, Ostrovsky, and Berry (2007).

[21] We also estimated the system using a demand shifter as an additional instrument in the pricing equation: the log of aggregate vehicle sales in a firm's home market. Results were similar but more sensitive to the exact sample period used.

[22] The mean effect of fuel efficiency was also estimated negatively in Berry et al. (1995).

[23] Including a quadratic quality term generates a positive but highly insignificant point estimate.

TABLE 5.—EMPIRICAL POLICY FUNCTIONS

	Marginal Cost Specification	
Dependent Variable: Patent Applications	Constant MC (1)	Log-Linear MC (2)
ξ_{jt}	0.48	1.93***
	(0.77)	(0.73)
ξ_{jt}^2	−0.98***	−3.28***
	(0.35)	(0.51)
ξ_{jt}^3	−0.15	−1.53***
	(0.43)	(0.44)
Rank of ξ_{jt}	0.04	−0.02
	(0.06)	(0.05)
Mean(ξ)	−1.14	9.48***
	(1.25)	(1.61)
S.D.(ξ)	−12.94***	−3.68
	(3.28)	(3.16)
Skewness(ξ)	−0.80***	1.00***
	(0.25)	(0.32)
Kurtosis(ξ)	0.42***	1.16***
	(0.10)	(0.16)
I.Q.R.(ξ)	5.16***	4.53***
	(1.52)	(1.60)
Maximum(ξ)	1.33	−3.45**
	(1.35)	(1.45)
Constant	5.12***	2.89***
	(0.64)	(0.60)
R^2	0.26	0.42
Observations	327	327

***: Significant at 1%, **: Significant at 5%.

reduce innovation once own quality is sufficiently high. Innovation is higher when the average quality in the industry is higher in specification (2), suggestive of a strategic response. Higher-quality dispersion in the industry also boosts innovation. This is true for the interquartile quality range and for higher kurtosis (fat tails). A more skewed distribution of quality boosts innovation, but the quality level of the leading firm has an opposite effect.

While some patterns are informative and intuitive, all of these effects interact. This policy function will be used to estimate the dynamic parameters, and based on those estimates, we can calculate the optimal policy vector that this function is approximating. The R^2 statistic indicates that the quality levels obtained using the log-linear specification of marginal cost, the benchmark specification, lead to a much better fit.

State Transitions. Each firm has two state variables in our model. The first one is the shock to the cost of innovation. We assume it to be i.i.d. over time and across firms and to follow a normal distribution with mean 0. Its standard deviation is one of the dynamic parameters of the model and is estimated in step 2.

The second state variable is the quality of a firm's vehicle relative to that of the peripheral firm. From one year to the next, it can go up or down one step or remain unchanged. Assume that a firm can be hit by a positive or negative shock that moves its quality up or down by one step. The probability of a positive shock is $p \in [0,1]$ and increasing in innovation. The probability of a negative shock is $d \in [0,1]$ and is due to a quality improvement by the peripheral firm. Such a negative shock affects the normalized quality level of all firms at the same time.

p and d are parameterized as follows:

$$d = \theta_{t1},$$
$$p = \exp(-\exp -(\theta_{t2}\ln(x_{jt}+1) + \theta_{t3}\xi_{jt} + \theta_{t4}\xi_{jt}^2)).$$

We do not impose any restrictions on θ_{t1} but expect it to be positive and less than 1. Using the cumulative density function (cdf) of a double exponential distribution for p ensures that it lies between 0 to 1. A positive effect of patenting on quality will be reflected in a positive value for the θ_{t2} parameter. The quadratic function of ξ_{jt} allows the probability of a quality improvement for a given level of innovation to vary across the quality spectrum. For example, it might become more difficult to improve one's quality further if it is high already. It can also incorporate idiosyncratic quality depreciation or regression to the mean.

Assuming that the two shocks are independent, we can derive the three transition probabilities in equation (11). The probabilities of quality moving up, moving down, or staying put are

$$p^U = p\,(1-d),$$
$$p^D = (1-p)\,d,$$
$$p^S = p\,d + (1-p)(1-d).$$

Together they fully define the transition function $P_\xi(\xi'|\xi, x)$.

However, these general transition probabilities do not automatically respect the finite state space. We have to exogenously restrict them at the boundaries: $p^U(\xi_{\max}) = 0$ and $p^D(\xi_{\min}) = 0$. This could also be achieved by choosing more involved functional forms for p and d, but we do not view these restrictions as very serious. We have discretized the quality range with the maximum far beyond what is reached over the sample period. The bounds do not limit the absolute quality levels, only the relative quality. Most important, the estimates imply that although innovation is positive over the full quality range, it becomes very low even before quality reaches the maximum level. The restriction is unlikely to affect innovation incentives greatly, also because firms innovate to avoid depreciation as well.

To estimate the state transition parameters, we first discretize the state variable ξ, which is continuous in the data. To keep the computational burden in step 2 manageable, we use a relatively coarse grid. ξ can take fifteen different values from −1.4 to 1.4 in steps of 0.2. This is sufficiently detailed to generate a correlation of 0.984 between the observed and discretized values. The maximum value in the data is 0.8, and there are only two observations (out of 340) for which the value of ξ equals the lower limit of −1.4.

As in Rust (1987), we estimate the state transition parameters by maximum likelihood. The coefficients in the first row of table 6 imply that a firm of average quality ($\xi = 0$) that

TABLE 6.—ESTIMATED TRANSITION PROBABILITY PARAMETERS

	Constant MC (1)	Log-Linear MC (2)
θ_{t1} (same as d)	0.547***	0.639***
	(0.046)	(0.085)
θ_{t2} (coefficient on x in p)	0.062**	0.126**
	(0.029)	(0.052)
θ_{t3} (coefficient on ξ in p)	−0.884***	−1.440***
	(0.243)	(0.442)
θ_{t4} (coefficient on ξ^2 in p)	−0.285	0.403
	(0.249)	(0.665)
Observations	327	327

***: Significant at 1%, **: Significant at 5%.

does not innovate has a 54.7% or 63.9% chance, depending on the specification, that its relative quality declines by one step.

Most important, innovation is found to boost the probability of reaching a higher-quality level. The effect is twice as large in the log-linear, benchmark case. It is also intuitive that the probability of going up one quality level is estimated lower for firms with higher-quality levels ($\theta_{t3} < 0$). As a result, a firm that aims for a particular probability of going up 1 quality step will need to innovate more if its existing quality is higher. The point estimates imply that a 1 standard deviation increase in innovation raises p^U by 2.1% and lowers p^D by 3.7%. Holding innovation constant, a 1 standard deviation increase in ξ lowers p^U by 6.1% and raises p^D by 10.8%.[24]

Computation of the value function. Combining all the building blocks with a set of initial values for the structural parameter vector θ_x^0, we can calculate the value function for any industry state $\mathbf{s} = \{\xi_1, \cdots, \xi_n, \nu_1, \cdots, \nu_n\}$. We do this by forward-simulating profit realizations.

We start from an initial industry state $\mathbf{s}_0$, the vector of observed quality levels for one year supplemented by a set of random draws on the cost shocks $\boldsymbol{\nu}$. We solve the system of first-order conditions, equation (8), with the estimated demand and cost parameters to obtain the equilibrium price vector. Market shares are then given by the demand equation (7) and both variables are substituted in the variable profit function (9).[25] The estimated policy function directly provides optimal innovation decisions for all firms. Subtracting the cost of innovation from variable profits gives a vector of values for all active firms in the initial year: $\boldsymbol{\pi}_0(\mathbf{s}_0) - c(\mathbf{x}_0, \mathbf{s}_0|\theta_x^0)$.

[24] The positive effect of patenting on quality can already be seen in the raw data, and it is quite strong. A 1 percent increase in patent applications is associated with a 0.25% increase in quality. Dividing quality into a quantity and price component, as in equation (7), reveals that the effect on price (0.45%) is stronger than on market share (0.12%).

[25] To save on computation, we assume that the shocks to marginal cost have 0 standard deviation. We also experimented with non-0 standard deviation of the shocks. We found that when the elasticity of demand is low, as it is in our estimated model, the expected profits with non-0 standard deviation are very similar to those with 0 standard deviation.

Next, we use the estimated transition probabilities to update the industry state. For each (x_j, ξ_j), we compute the three probabilities in equation (11) and then draw a realization of ξ_j' from the appropriate distribution. With a new set of draws on ν, this gives $\mathbf{s}_1$, the industry state in the next year. Following the same steps as above, we can compute the expected net profit for each firm in period 1.

This process is repeated T periods. We have set the discount factor to 0.95 and T to 150 periods ($\beta^{150} = 3.7e - 6$). The value functions are then simply the present discounted values of these profit streams,

$$V(\mathbf{s}_0|\theta_x^0) = E\left[\sum_{t=0}^{T} \beta^t[\boldsymbol{\pi}_t(\mathbf{s}_t) - c\left(\mathbf{x}_t, \mathbf{s}_t|\theta_x^0\right)]\right], \tag{13}$$

where the expectation is over future states. We perform these forward simulations 2,000 times using different draws for the $\boldsymbol{\nu}$ shocks and the realizations of the state transitions. The average over all simulations is the numerical estimate of $V(\mathbf{s}_0|\theta_x^0)$. We repeat this for all observed industry states by taking each as the starting state for a separate set of simulations.

B. *Step 2*

The final step is to estimate the dynamic parameters of the model using the minimum distance estimator proposed by Bajari et al. (2007). Let $\chi_j^*(\xi_j, \xi_{-j}, \nu_j|\chi_{-j}^*)$ be the Markov Perfect Equilibrium policy profile for firm j. If this is an equilibrium strategy, the value from following it must be at least as high as from following any alternative strategy χ_j':

$$V_j(\xi_j, \xi_{-j}, \nu_j|\chi_j^*, \chi_{-j}^*, \theta_x) \geq V_j(\xi_j, \xi_{-j}, \nu_j|\chi_j', \chi_{-j}^*, \theta_x). \tag{14}$$

Note that firm j deviates from the MPE strategy, while its rivals still follow their Nash strategies. Equation (14) will hold at the true parameter vector θ_x^*.

Using the forward simulation procedure described above, we can calculate the value function for both the optimal and alternative policy profiles. The difference $d(\xi_j, \xi_{-j}, \nu_j|\chi_j', \theta_x) = V_j(\xi_j, \xi_{-j}, \nu_j|\chi_j^*, \chi_{-j}^*) - V_j(\xi_j, \xi_{-j}, \nu_j|\chi_j', \chi_{-j}^*)$ enters the objective function of the minimum distance estimator only if it is negative, that is, when the equilibrium condition (14) is violated. Conditional on θ_x, we calculate these differences for all firms j, industry states $\mathbf{s}$, and alternative policies χ'. $\hat{\theta}_x$ is then chosen to minimize the sum of the squared negative terms to minimize violations of the MPE:

$$\hat{\theta}_x^* = \arg\min \sum_{j,\mathbf{s},\chi'} \left[\min\{d(\xi_j, \xi_{-j}, \nu_j|\chi_j', \theta_x), 0\}\right]^2. \tag{15}$$

The alternative policies used in the estimation are the following deviations from the equilibrium Nash policy: $\chi_j' = (1 + \iota)\chi_j^*$, where ι takes the following four values:

TABLE 7.—ESTIMATED DYNAMIC PARAMETERS

	Constant MC (1)	Log-Linear MC (2)
θ_{x1} (coefficient on x)	5,141***	2,652***
	(347.2)	(96.17)
θ_{x2} (coefficient on x^2)	−4.430***	−0.060***
	(0.795)	(0.009)
θ_{x3} (coefficient on x^3)	0.724e–3**	0.209e–6***
	(0.336e–3)	(0.046e–6)
θ_{x4} (coefficient on $\tilde{\nu}x$)	884.4	309.6
	(2422)	(302.8)

Minimum distance estimates. Standard errors are bootstrapped. ***: Significant at 1%, **: Significant at 5%. Using a wider range of perturbations, ι = [.6 .7 .8 .9 1.1 1.2 1.3 1.4], we obtain similar point estimates, respectively, 2,530, −0.057, 0.195e-6, and 267.7.

[0.90 0.95 1.05 1.10].[26] We parameterize the cost of R&D function as:

$$c(x_j, \nu_j|\theta_x) = \underbrace{\left(\theta_{x1} + \theta_{x2}x_j + \theta_{x3}x_j^2 + \theta_{x4}\tilde{\nu}_j\right)}_{\text{cost per patent}} x_j, \tag{16}$$

where $\tilde{\nu}_j$ is a standard normal variable and $\theta_{x4}\tilde{\nu}_j = \sigma_\nu\tilde{\nu}_j = \nu_j$.

Standard errors for the estimates in table 7 are bootstrapped following the procedure in Bajari et al. (2013), which ignores sampling error in the first stage. The most important implication of these estimates is that the average, as well as the marginal, cost of R&D is declining in the number of patents. The decline is less pronounced in the benchmark case of log-linear marginal production costs.

These point estimates imply an average cost per patent of \$3.6 million if we assume constant marginal costs and \$2.6 million when marginal costs are increasing in quality. This difference is intuitive. In the log-linear case, the net benefit of innovation is reduced because a higher quality level—the ultimate reason that firms innovate—raises the firm's marginal production costs. It makes patents less valuable, all else equal, and the model can rationalize the observed rate of patenting with a lower cost of innovation.[27]

For a subset of the firms in our sample, we have obtained information on total R&D expenditure from consolidated accounts in the COMPUSTAT database. It implies average R&D expenditures per patent application of \$8.4 million. This is higher, but of the same order of magnitude as our estimates. It is plausible that firms derive benefits from patenting beyond those that we have included in our model. This can include licensing revenue, obtaining benefits in other sectors where these firms are active, or raising a firm's value as a takeover target. Including such benefits in the model would lead to higher cost estimates to rationalize observed patenting rates.

V. Market Structure and Innovation

A. *Computation of Equilibrium*

We now turn to our main question of interest. How does innovation in the global automobile industry depend on the intensity of competition or the market structure generally? In principle, one could investigate this using the estimated policy function from the first stage of the estimation procedure, as in Benkard et al. (2010).[28] In the global automotive industry, we do not observe nearly enough information to characterize the subtle effects without imposing some theory. In practice, then, we have to calculate the MPE using the estimated primitives and our fully specified model. This provides us with optimal innovation strategies in all possible market structures.

One benefit of this approach is that one can also use it to investigate the sensitivity of any pattern to different parameter values. Goettler and Gordon (2014) explicitly study the response of innovation to exogenous changes in product market competition, investment spillovers, and the entry cost distribution by solving a similar model for a variety of parameter values. A second benefit is that we are not limited to studying only the very narrow range of market structures observed over the sample period. If we simulate the evolution of the industry forward, we see that a wide range of market structures is visited for relatively brief periods.[29]

To calculate the MPE, we follow the algorithm of Pakes and McGuire (1994) and provide some of the details in the appendix. The computational burden has three sources: the size of the state space, the computation of the continuation values, and the number of iterations to convergence. Using fifteen possible values for ξ and assuming it can transition to three possible values in the next period, it takes approximately two days to compute the equilibrium for five firms.[30] Note that this allows 243 (= 3^5) possible values for the industry state in the next period. We demonstrate below that this equilibrium already contains rich dynamics to inform us on the question of interest.[31]

To gauge the fit of the model, we repeatedly draw five firms randomly from the sample and compare the optimal innovations for that industry state to the observed innovation

[26] Using more perturbations is desirable, but it raises the computational burden proportionately. As a robustness check, we doubled the number of perturbations and reestimated the dynamic parameters. We report the results of that exercise in the notes to table 7. Srisuma (2010) shows that with additive disturbances, even an infinite number of alternative policies does not guarantee identification, but with the multiplicative perturbations that we use, that problem is avoided, at least if the support of the disturbances is sufficiently large.

[27] There are offsetting effects, as the price elasticity is estimated higher and the effectiveness of innovation to raise product quality is estimated lower in the constant MC case. These changes also decrease the net benefit of patenting and help match observed rates of patenting.

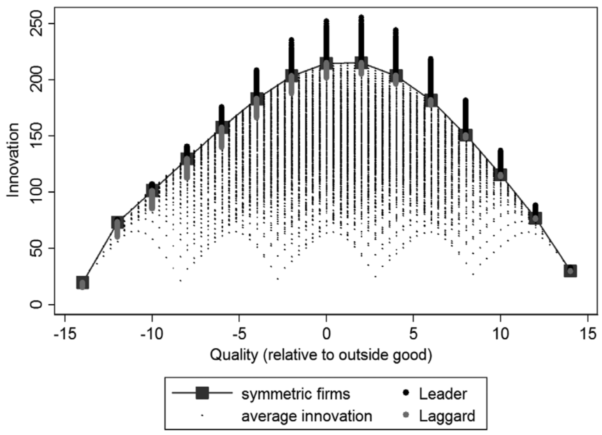
[28] Studying the U.S. airline industry, they assume that the route network is only important locally and can be treated as predetermined. In that case, thousands of markets (city-pairs) all provide independent information on firm behavior that is used to characterize the policy function.

[29] In figure A.2 of Hashmi and Van Biesebroeck (2012), we illustrate that the average efficiency level for active firms can change dramatically over a short period of time.

[30] We restrict the computation of equilibrium to five firms for tractability reasons. As the number of firms increases, the size of the state space and, hence the computational burden, increases exponentially.

[31] For a dynamic game of this size, multiple equilibria are the rule rather than the exception. We compute just one possible equilibrium, but for the few sets of starting values that we tried, the algorithm always converged to the same equilibrium.

FIGURE 2.—RELATIONSHIP BETWEEN INNOVATION AND A FIRM'S OWN QUALITY



data and the predictions from the empirical policy function, equation (12). The pairwise correlations between the optimal policies and both benchmarks are rather high: with the data, it is 0.64 and with the empirical prediction, it is 0.55.[32]

B. *Equilibrium Relationship between Market Structure and Innovation*

We now use the equilibrium strategies of the dynamic game to investigate the relationship between market structure and innovation in the global automobile industry. We characterize the industry by a benchmark firm that does not behave strategically, representing a fringe of competitive firms, and five firms that invest strategically.[33] The first three figures—figures 2, 3 and 4—highlight that even our simple model predicts a wide range of optimizing behavior by taking into account that firms are forward looking and behave strategically. They illustrate the impact of competition on a firm's innovation incentives, holding gradually more aspects of the market structure constant. In the next section, we simulate the impact of entry on the incumbents' innovation incentives.

Figure 2 plots a firm's innovation against its own quality, the state variable ξ_j.[34] For each value, there is a range of optimal innovation choices as the exact value depends on the market structure a firm faces. The square markers depict choices when the five (strategic) firms are symmetric; recall that the peripheral firm's quality is always normalized to 0. Innovation clearly traces an inverted-U shape. This inverted-U is at the firm level, as opposed to the one in Aghion et al. (2005), who found a similar relationship at the industry level. In figure 6, we turn to the effect of increased competition on industry innovation.

Both the positive relationship between innovation and quality at the left side and the negative relationship at the right side can be rationalized directly from the primitives of the model. The benefit of innovation is to raise the probability of a quality improvement. The estimated state transition process implies that a firm needs to raise its level of innovation to attain the same benefit if its current quality level is higher. This is one force leading to a positive relationship. Given the stochastic depreciation of quality, innovation is necessary even to maintain quality. The declining R&D cost per patent makes it easier to innovate sufficiently to counter depreciation and is a second factor leading to a positive relationship.

At the same time, the value of a higher quality to the firm is not constant either. It raises demand, but also marginal production cost. As the latter increases convexly in ξ, variable profits will eventually become concave in quality and further improvements will be less valuable. This is an important factor explaining the negative relationship on the right. A different quality level also influences the innovation strategies of a firm's rivals, but it is not obvious to determine how this effect leads to variation in innovation incentives over the quality spectrum.

Over most of the quality range, the maximum optimal innovation is approximately one-quarter above the minimum level. At intermediate quality levels, innovation is not only higher, the optimal strategies are also a lot more dispersed in absolute values. At higher quality levels, the range is more compressed. The range of optimal innovation in figure 2 is determined entirely by the varying effect of quality on demand and by strategic interaction as the production and innovation costs as well as the state transitions are only a function of own quality.

Conditional on the level of own quality, innovation is higher when a firm is a market leader (the smaller black circles) than if it lags the industry (gray circles). Innovation in the case of symmetric firms tends to be at the bottom end of the range, except for the lowest quality levels. The range of innovation is also wider for leaders. The dispersion is highest at $\xi = 8$ for the leader, with the $x_{\max}/x_{\min}$ ratio equal to 1.21. For laggards, the dispersion is decreasing in own quality, and for firms in the middle of the industry, dispersion is almost constant over the entire range.

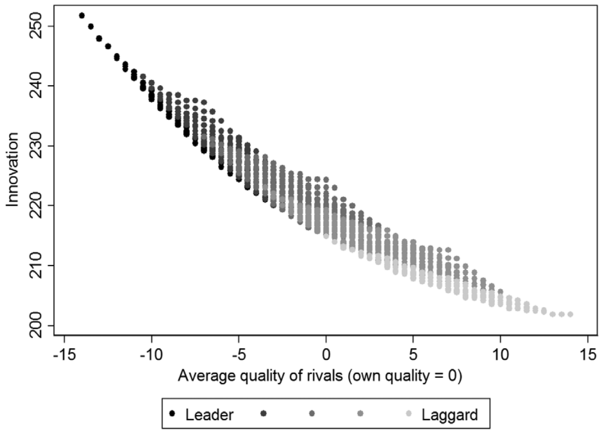
The small dots in figure 2 show average innovation across all active firms as a function of their average quality on the horizontal axis. Because innovation is concave and eventually even decreasing in own quality, as described above, average innovation is highest in the symmetric case. Nowhere in the quality spectrum does the additional innovation of a higher-quality firm compensate fully for the reduced innovation of a quality laggard. Because innovation does not rise monotonically with own quality, the dots cover a much wider range than the solid markers. In the extreme, innovation by symmetric firms can be up to eight times higher

[32] The correlation between the data and the empirical prediction is 0.48, which is comparable to the R^2 of 0.42 in table 5.

[33] Firms' investment decisions also depend on their private cost of R&D realizations. We use the expected level of innovation given the distribution of the cost shock ν.

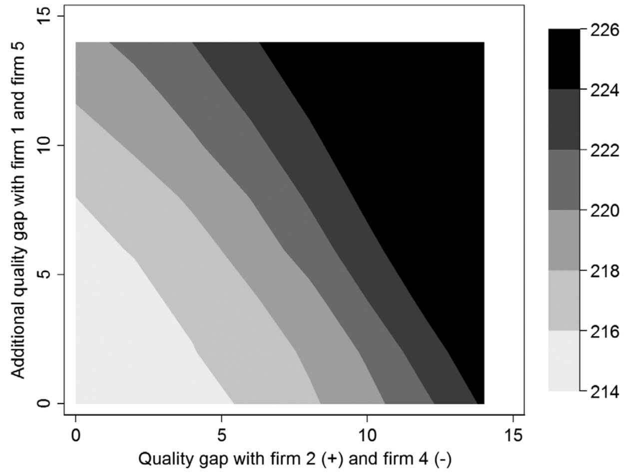
[34] The range of own quality is from −1.4 to 1.4 in increments of 0.2. For display purposes, in figure 2 and all subsequent figures, we transform this range into the one from −14 to 14 in increments of 2.

FIGURE 3.—RELATIONSHIP BETWEEN INNOVATION AND RIVAL QUALITY



Quality of the firm whose innovation is shown is held constant at 0.

FIGURE 4.—RELATIONSHIP BETWEEN INNOVATION AND QUALITY DISPERSION



Quality of the firm whose innovation is shown, as well as the average quality of its rivals, is held constant at 0.

than average innovation in an industry with the same average quality level but maximum inquality between active firms.[35] This highlights the sensitivity of innovation to own quality and the importance of holding own quality constant, which we do in all subsequent figures.[36]

In figure 3, we only show optimal innovation for a firm with 0 quality, the same as the outside good, but for different market structures. On the horizontal axis, we plot the average quality of its rivals, and the shading of the markers indicates the firm's rank in the industry. Optimal innovation ranges from 202 to 252 patents.[37]

The dominant pattern is for innovation to be higher when a firm faces weaker rivals, and the differences can be quite substantial. For example, a leading firm will lower its innovation by twelve to thirteen patents when the average quality of its rivals is raised from -14 to -10. At least in this particular dimension (total or average quality of a firm's rivals), innovation is declining in competition.[38]

Along a vertical line, meaning for a given average quality level of a firm's rivals, the markers tend to be darker at the top. It suggests that firms innovate more when their own quality rank in the industry is higher, keeping own and average quality levels constant. There is one exception: when the average quality is low, the second firm innovates more than the industry leader.

In most cases, there is still a wide range of optimal policies. For a leading firm, optimal innovation ranges from 215 to 252, depending on the quality of its rivals. This overlaps a lot with the optimal innovation policy for a firm in the middle, which ranges between 208 and 232. If we hold rivals' quality constant, the range narrows, but for $\overline{\xi}_{-i} = 0$, optimal innovation for firm i still varies between 214 and 225.

In figure 4, the variation within this last range is illustrated further. We show innovation for the middle firm (firm 3) whose own quality level is 0. The lines show the contour plots for different innovation levels as a function of a mean-preserving increase in quality dispersion. Along the horizontal axis, the gap between firm 3 and its neighbors (2 and 4) is increased. Along the vertical axis, the additional distance to the overall leader and laggard (firms 1 and 5) is shown. As a result, the innovating firm's own quality and rank in the industry, as well as the average rival quality, are held constant.

Innovation is lowest in the symmetric case (the bottom-left corner) when all firms have 0 quality. Away from the origin, innovation becomes higher as dispersion increases. The contour lines have a slope steeper than -1, indicating that raising the gap with the firms at the extremes has a similar but smaller effect. Moreover, as rival firms differ more in quality, the contour lines in figure 4 become steeper, suggesting that innovation incentive becomes smaller as the quality gap becomes too large.

Whether aggregate innovation increases or decreases depends crucially on where we conduct this exercise of a mean-preserving increasing in quality dispersion. On the one hand, innovation is higher when firms are in the middle of the quality range. On the other hand, innovation is higher when rivals are farther from one another. In figure 4 the former effect dominates, and moving rivals to the quality extremes lowers their innovation more than it boosts the innovation of the intermediate firm.

These effects also lead to a positive relationship at the industry level between concentration in quality and innovation. When quality becomes more concentrated in a few

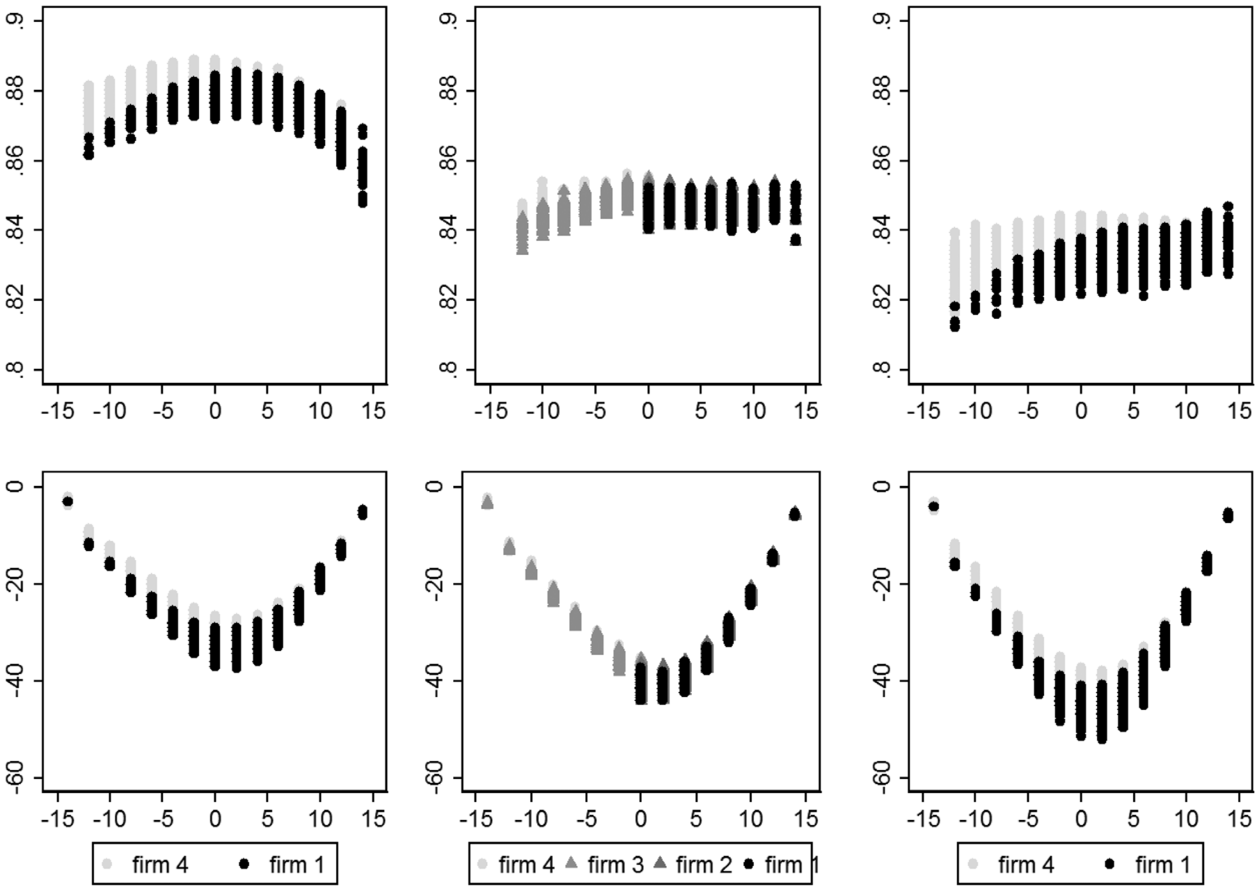
[35] As an example, if one firm is at $\xi = -14$ and a second one at $\xi = 14$, average innovation would be below 50. In contrast, two symmetric firms with $\xi = 0$ would apply for more than 200 patents each.

[36] Cohen (2010) stresses that a failure of empirical scholars to control for relevant contingencies is one reason that the existing evidence on the Schumpeterian hypothesis is inconclusive. At the firm level, controlling for own quality is perhaps the most important contingency.

[37] The range is equally wide for quality levels -2 or $+2$ but gradually narrows for more extreme quality levels.

[38] This effect is opposite of the sign on mean(ξ) in table 5, but a change along the horizontal axis of figure 3 influences other variables in the estimated policy function as well.

FIGURE 5.—CHANGE IN OPTIMAL INNOVATION FOR INCUMBENTS AFTER ENTRY



In the different columns, the new entrant has quality level −14 (left), 0 (middle), or +14 (right). The top graphs show the ratio of optimal innovation for some incumbents in the market structure with five versus four active firms. The bottom graph shows the difference in innovation.

firms, it raises the concentration in innovation at a more than proportional rate. However, it also reduces total innovation in the industry.[39]

C. *Counterfactual Analysis: The Effect of Entry*

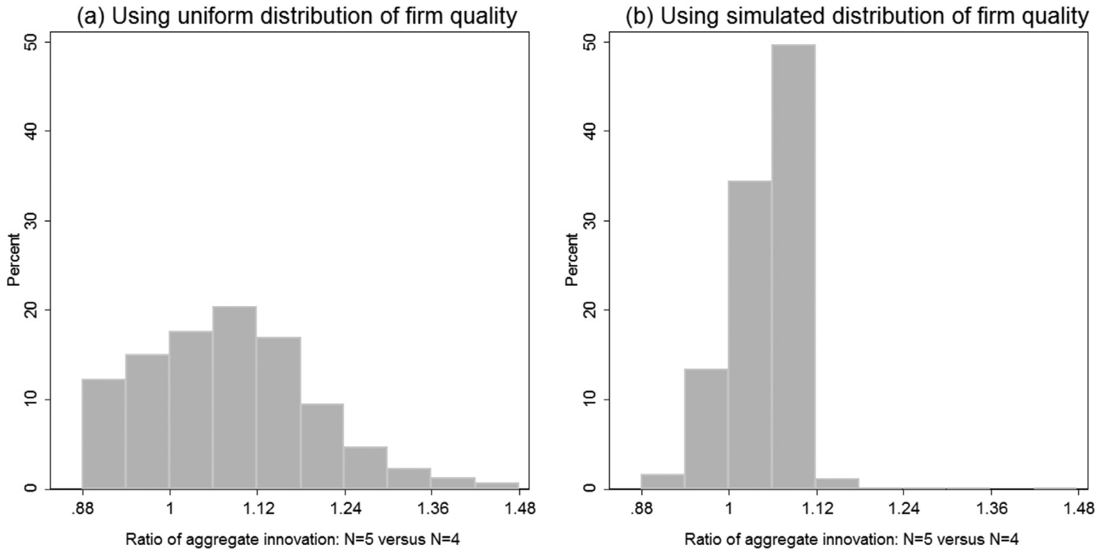
We now analyze a counterfactual simulation where an additional firm enters the industry. For all possible market structures with four active firms, we calculate how this changes the optimal innovation of incumbents, holding their quality levels constant. In the three columns of figure 5 we show different situations, adding the new firm, respectively, at the minimum quality level, exactly in the middle, or at the maximum quality level. The top graphs show the relative innovation of incumbents in the situation with five versus four active firms and the bottom graphs the absolute difference in desired patents.

The most important pattern to note is that all ratios are less than 1 and all differences are negative. Incumbents always choose to innovate less when faced with an additional competitor. We believe this is to a large extent driven by the demand function and the nature of price setting in our model. Each active firm will be able to capture some market demand, even if its product is relatively unattractive to the average consumer. This takes market share away from its rivals and will blunt their innovation incentives. This property of the logit function is well known (see, e.g., Petrin, 2002) and is shared by most discrete choice models. Ackerberg and Rysman (2005) suggest a way to counteract it, which is especially relevant if one is interested in welfare comparisons with different number of products.

It is intuitive that the decline in innovation is increasing in the quality of the entrant (i.e., smallest in the graphs on the left and most pronounced on the right). This is especially true for the weakest firms, which are depicted in lighter shades. On average, innovation is 16% lower, but declines ranging from 11% to 19% are observed. The average decline is 40% higher following a high-quality entrant than a low-quality entrant. This difference is much larger for firms that are themselves of low quality. The absolute decline in patenting is always largest for firms with quality around 0, because their rate of innovation is highest. Such a firm will aim for at least 26 fewer patents, but the reduction can be as large as 52 fewer patents.

[39] This pattern is shown in figure A.4 of Hashmi and Van Biesebroeck (2012), and it still holds using the current estimates.

FIGURE 6.—CHANGE IN AGGREGATE INNOVATION WITH ONE EXTRA FIRM



Holding own quality constant, the darker markers tend to be at lower values in most panels, suggesting that leading firms respond more to entry than lagging firms do. As a result, entry will slightly reduce the innovation difference among incumbents. In our model, the efficiency effect dominates the replacement effect, and innovation incentives are reduced as the number of active firms increases in a market of constant size. Firms do take some market share away from the outside good, but it is not enough to compensate for the additional competition. This holds more strongly for industry leaders than for followers.

Of course, the innovation performed by the newly entered firm contributes positively to aggregate innovation in the industry. Whether this effect outweighs the reduced innovations by incumbents depends crucially on the quality of the entrant. If incumbents have extreme qualities, either high or low, their absolute decline in innovation would be small anyway. A new firm entering in the middle of the quality distribution would aim for up to 250 patents and certainly would raise aggregate innovation. To verify how likely this is, we have calculated aggregate innovation in all possible market structures with four active firms and compare this to the aggregate innovation with one extra firm.

In the left panel of figure 6, we plot the histogram of the ratio of aggregate innovation in the two cases using uniform weights for all possible initial market structures and for any possible quality level for the entrant. In almost three-quarters of the cases, aggregate innovation goes up. The additional innovation provided by the entrant outweighs the declining innovation of the four incumbents. Given the 16% average decline that we found in figure 5, this finding is plausible. If innovation declines, it does so by at most 12%. In a few cases, the increase is extremely high, but this happens only when initial innovation is very low. In approximately 1% of the cases, innovation increases by more than half. The average increase, when positive, is 14%.

However, not all market structures or quality levels for a new entrant are equally likely. In the right panel of figure 6, we use more realistic weights to construct a similar histogram for the change in aggregate innovation. We now use the optimal innovation policies and the estimated transition process for quality to simulate forward 200 years for 100,000 randomly drawn market structures. We discard the first 100 years and use the remaining to calculate frequency weights for all possible market structures. The quality of a new entrant is drawn from the frequency distribution of the third firm in a market structure with four active firms. This reflects that firm quality is the result of a string of past innovation decisions, and a new firm is unlikely to enter right away with a quality drawn from the average quality distribution across all active firms. Using these weights, we find that the probability that aggregate innovation increases is even higher. In fully 86% of all cases, aggregate innovation does increase, but the average increase is only 6.3%.

The analysis in Aghion et al. (2005) showed for U.K. manufacturing that industry innovation has an inverted-U relationship with the strength of competition within an industry. Increased competition raises innovation in an industry that is monopolized but reduces innovation when competition is already high. Our results indicate that both effects are indeed possible. They also suggest that the former effect is a lot more likely for an industry characterized by the demand and cost features that we estimated for the automobile industry. Especially when we take into account the likelihood of observing the different market structures, it is relatively rare for more competition—in our case entry of a new firm—to reduce industry innovation.

VI. Conclusion

We have accomplished two things. First, we estimated all parameters in a structural game-theoretic model of strategic, forward-looking, innovating firms for the automobile sector. Second, we calculated the optimal Markov Perfect Equilibrium policy for this game for all possible states of the industry and used it to investigate how optimal innovation responds to exogenous changes in market structure.

The structural approach in this paper has a number of advantages over more reduced-form approaches. It allows us to focus on the equilibrium relationships without worrying about endogeneity of market structure or reverse causality of innovation on market structure. In fact, the structural approach addresses the endogeneity problem directly by embedding those two-way interactions explicitly in the model. Nonmonotonic effects can also be straightforwardly dealt with by holding some aspects of market structure constant while varying others. Finally, it allows us to study the relationship across a wider range of industry states than observed in the data.

Our approach is complementary to theoretical work studying the same question. While it is useful to know what types of effects are possible in a model of profit-maximizing firms, it is equally important to know which of these effects matter most in a model where the primitives are estimated from the data. We used functional forms for demand and marginal costs and a price-setting assumption that are widely used in static models of the automobile sector. The implementation to the global industry and in a dynamic model necessitated some additional assumptions, but the estimated model, and the policy vector in particular, is consistent with the observed data.

In terms of substantive findings, the parameter estimates in the demand, marginal cost, and state transition equations are all plausible. Most important, the benchmark model implies average R&D expenditure of approximately $2.6 million per patent (higher if marginal costs are assumed to be constant). The average cost per patent is decreasing in the rate of patenting, which is consistent with the R&D data. It is obvious that firms will innovate more when they get a low private draw on the cost of innovation, but the decreasing pattern even holds for the common part of the cost of R&D function.

Several of the equilibrium patterns we uncover are supportive of the Schumpeterian hypothesis that increased competition leads to lower innovation. Faced with rivals of higher quality, firms cut back on their own innovation, even though those high-quality rivals are not necessarily innovating very intensively themselves. Firms innovate more when operating in a market with highly dispersed quality levels, holding average quality constant. Following entry, incumbents invariably reduce their own innovation. Aggregate innovation still increases in most cases because the added innovation by the new entrant outweighs the reduction of all incumbents. Given that the Schumpeterian hypothesis is quite controversial, it is remarkable that we find these effects using functional forms that are widely used in empirical work.

One limitation of our model is the assumption of i.i.d. shocks to the cost of R&D. Direct inspection of the data shows some differences in innovation across firms to persist over time, which could be due to the heterogeneous costs of R&D. Some firms are consistently better at innovating than others. Incorporating persistent shocks would increase the state-space that firms condition innovation decisions on. It would also make it harder to rationalize those shocks being entirely private, but we believe that this is an interesting area for future research.

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APPENDIX

Implementing the Pakes-McGuire algorithm

The Pakes-McGuire (PM) algorithm starts with arbitrary value and policy functions V^0 and X^0 that are defined over the entire admissible state space. We update these functions pointwise and iterate until they converge to their equilibrium values. The updating goes as follows.

For firm j in state (ξ_j, ξ_{-j}, ν_j), we find its equilibrium level of innovation given V^0 and X^0_{-j}. Differentiate the right-hand side of the Bellman equation (10) with respect to x_j:

$$\frac{\partial c(x_j, \nu_j)}{\partial x_j} = \beta \frac{\partial EV^0\left(\xi_j', \xi_{-j}', \nu_j'\right)}{\partial x_j}.$$

We assume the cost of R&D function to take the following form:

$$c(x_j, \nu_j) = \underbrace{\left(\theta_{x1} + \theta_{x2} x_j + \theta_{x3} x_j^2 + \theta_{x4}\tilde{\nu}_j\right)}_{\text{cost per patent}} x_j.$$

This gives the following expression for the left-hand side of the first-order condition (FOC) above:

$$\frac{\partial c(x_j, \nu_j)}{\partial x_j} = \theta_{x1} + 2\theta_{x2} x_j + 3\theta_{x3} x_j^2 + \theta_{x4}\tilde{\nu}_j$$

To find the derivative on the right, first note that

$$\begin{aligned} EV^0\left(\xi_j', \xi_{-j}', \nu_j'\right) = {} & p^U EV^0\left(\xi_j + \Delta_\xi, \xi_{-j}', \nu_j'\right) + p^S EV^0\left(\xi_j, \xi_{-j}', \nu_j'\right) \\ & + p^D EV^0\left(\xi_j - \Delta_\xi, \xi_{-j}', \nu_j'\right). \end{aligned}$$

The derivative, after some simplification, is then given by

$$\frac{\partial EV^0\left(\xi_j', \xi_{-j}', \nu_j'\right)}{\partial x_j} = \frac{b_2}{x_j + 1} A e^{-B\left(x_j, \xi_j\right) - e^{-B\left(x_j, \xi_j\right)}},$$

where

$$\begin{aligned} A = {} & (1 - \theta_{t1})\left[EV^0\left(\xi_j + \Delta_\xi, \xi_{-j}', \nu_j'\right) - EV^0\left(\xi_j, \xi_{-j}', \nu_j'\right)\right] \\ & + \theta_{t1}\left[EV^0\left(\xi_j, \xi_{-j}', \nu_j'\right) - EV^0\left(\xi_j - \Delta_\xi, \xi_{-j}', \nu_j'\right)\right], \end{aligned}$$

and

$$B\left(x_j, \xi_j\right) = \theta_{t2} \ln\left(x_j + 1\right) + \theta_{t3}\xi_j + \theta_{t4}\xi_j^2.$$

Substituting the two derivatives into the FOC and simplifying, we get the following equation that implicitly defines optimal innovation:

$$\theta_{x1} + 2\theta_{x2} x_j^* + 3\theta_{x3} x_j^{*2} + \theta_{x4}\nu_j = \frac{\beta\theta_{t2}}{x_j^* + 1} A e^{-B\left(x_j^*, \xi_j\right) - e^{-B\left(x_j^*, \xi_j\right)}}. \tag{A1}$$

The right-hand side in equation (A1) is the marginal benefit of having one more patent. It is decreasing in x if $\theta_{t2} > 0$ (i.e., if more patents lead to a higher probability of a firm's quality going up). Our estimates of state transition parameters indicate that this is indeed the case and $\hat{\theta}_{t2} > 0$. The left-hand side is the marginal cost of having one more patent. It is a quadratic function of the number of patents x, and its relationship with x depends on the dynamic parameter estimates. For our benchmark case (log-linear marginal cost), the left-hand side is increasing in x at the estimated parameters and enables us to find a unique solution to the equilibrium number of patents.

Once we know the optimal x_j^*, we can substitute it on the right-hand side of the Bellman equation to update the value function:

$$\begin{aligned} V^1\left(\xi_j, \xi_{-j}, \nu_j\right) = {} & \pi\left(\xi_j, \xi_{-j}\right) - \underbrace{\left(\theta_{x1} + \theta_{x2} x_j^* + \theta_{x3} x_j^{*2} + \theta_{x4}\tilde{\nu}_j\right)}_{\text{cost per patent}} x_j^* \\ & + \beta EV^0\left(\xi_j', \xi_{-j}', \nu_j' | \xi_j, \xi_{-j}, x_j^*\right). \end{aligned}$$

We continue to update the value and policy functions until the latter converges.