Competitive Pressure and Innovation Complementarities*

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Abstract

We build and estimate an equilibrium model of profit maximization to study whether firms change their strategies regarding different innovation activities following an increase in competitive pressure when complementarities among the innovations and other strategies may exist. The main contribution of the paper is to identify the transmission channels through which competitive pressure affects innovation activities. Using data from the French automobile dealer industry, we find that an increase in competitive pressure leads to an increase in product innovation and a decrease in process innovation, but only as an indirect effect through the expansion of the scale of production that follows market expansion after liberalization. Estimations always favor specifications that include unobserved returns to firm strategies. Results are robust to the definition of local markets, their size, their degree of urbanization, and any possible anticipation of the liberalization process that took place in the European automobile distribution system in September 2002.

Keywords: Competitive Pressure, Complementarity, Product and Process Innovation.

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1 Introduction

Innovations ultimately determine the growth possibilities of an economy through the provision of a higher variety of products and services of better quality. Whether monopoly favors the adoption of innovations more or less than competition is a classic question in Economics.[1] The answer to this question is of the utmost importance to help design optimal innovation and competition policies. Despite the common empirical practice however, it is important to recognize that innovations are only a subset of the strategies firms choose, that innovations are different in nature, and that they may interact to generate complementarities. The interdependence between the scale of production and innovations seems especially important; innovations may shift the minimum efficient scale, and larger firms may favor adopting different types of innovation than smaller ones.

What is the effect of an increase in competitive pressure on innovation decisions? To answer this question we study the adoption of different types of software using a database of French automobile dealers. Specifically, we ask: *How is competitive pressure transmitted?* Our model builds on four basic pillars: (*i*) we distinguish between demand enhancing and cost reducing innovations; (*ii*) we allow firms to make innovation decisions simultaneously with other strategies, most importantly the scale of production; (*iii*) we let these strategies generate return synergies when used jointly; and (*iv*) our estimations control for the possibility that unobservable factors drive the observed correlations between innovation strategies and scale of production.

Our results show that ignoring the endogeneity of the scale of production will wrongly attribute the adoption of innovations to an increase in competitive pressure. They indicate that the direct effect of an increase in competition on the likelihood of adopting innovations is negligible. We document that liberalization of the automobile distribution industry in Europe leads to an increase in the optimal scale of production, which in turn facilitates the adoption of product innovations but not process innovations. In fact, product and process innovations appear to be substitutes and therefore dealers specialize in adopting only one of the two. Ignoring these interdependencies could have led us to conclude that liberalization of this industry had no effect on innovations at all. Results are robust to the existence of unobserved returns to each strategy, as well as to the definition of local markets, their size, their urbanization, and any possible anticipation of the liberalization process that took place in the European automobile distribution system in September 2002.

Theoretical models are ambiguous in several ways regarding the effect that market structure may have on the innovativeness of firms. The traditional Schumpeterian view argues that firms

[1] Kamien and Schwartz (1982, §1) concisely summarize the historical debate on economic incentives to innovate from René Descartes and Adam Smith to Joseph Schumpeter and the post World Word II contributions.

with market power have the strongest incentive to innovate as their monopolistic position allows them to capture innovation rents. However, it is not clear that lacking this monopolistic position automatically reduces the incentive to innovate. Markups are smaller in competitive environments, boosting demand as more cost efficient firms may sell a lot more at lower prices. Furthermore, in the case of product innovations, competitive pressure may lead to additional product differentiation, which increases the sustainable markup that firms can effectively charge to their customers. The list of issues adding to these ambiguous predictions seems endless. For instance, Gilbert (2006) argues that competition may reduce the incentive to innovate if intellectual property rights are nonexclusive but it will foster innovation if property rights are exclusive. Schmutzler (2007) points to the countervailing effect of own demand shifts due to a competitor's adoption of a cost reducing innovation if products are complements, although the effect becomes reinforcing if they are substitutes. Finally, and without trying to be exhaustive, Vives (2008) stresses that incentives to innovate differ depending on whether entry is free or restricted. With this canvas of possibilities, it is not surprising that Gilbert (2006, §I) notices that *"... empirical studies rarely account for the many factors that the theory suggests should be significant determinants of innovative activity."* Indeed, Gilbert (2006, §II) acknowledges that *"It is not that we don't have a model of market structure and R&D, but rather that we have many models and it is important to know which model is appropriate for each market context."* Thus, contrary to the common practice of pooling data across industries and countries, empirical analysis should take into acccount the above arguments by focusing on institutions and features of specific industries.[2]

We find it useful to distinguish between demand enhancing and cost reducing innovations.[3] Not only are innovations diverse in their nature and goal but their adoption may follow different decision processes. Different schools of thought also have alternative takes on how market characteristics(including competition) affect either of these. Schmookler (1959) already stressed the different effect that market size has on the adoption of product and process innovations. Schumpeter (1934)

[2] In order to identify the effect of competitive pressure, researchers have used data sets that include several industries with different degree of competition, or the same industry across different countries. A general concern with these approaches is that econometric models fail to be closely linked to the institutional features of any industry in particular and results are suspicious of being driven by aggregation across industries and countries. For instance, Aghion, Blundell, Griffith, Howitt, and Prantl (2004) use a micro-level panel data of U.K. firms from several industries to evaluate the effect of foreign entry on domestic patenting decisions; Bresnahan (1995) analyzes how imports and inward foreign direct investment affects product and process innovation across industries in West Germany; Carlin, Schaffer, and Seabright (2004) evaluate the innovation performance of several State owned firms in twenty-four transition countries; and MacDonald (1994) studies how the rate of growth of labor productivity changes with import penetration using data from ninety-four industries in the 1972-1987 period. Two notable exceptions are the works of Galdón-Sánchez and Schmitz (2002), who make use of a well defined natural experiment in the iron-ore market, and Blundell, Griffith, and Van Reenen (1999), who make use of lagged information in a panel data estimation to control for the endogeneity and simultaneity of R&D expenditures and market structure.

[3] Boone (2000), Levin and Reiss (1988), and Rosenkranz (2003) also distinguish between demand and cost shifters in the context of product and process innovations.

argues that market power favors cost reducing innovations because larger firms may enjoy economies of scale and secure the appropriability of returns to investment. Conversely, Arrow (1962) argues that competitive environments provide the right incentives to adopt demand enhancing innovations that help firms differentiate their product offerings.

Also, innovations are only one of the many strategies that firms choose together with production, pricing, advertising, *et cetera*. Following Milgrom and Roberts (1990), we envision firms as organizational systems where several decisions are made in a coordinated manner. Firms will then benefit from taking into account the potential synergies that one strategy may have on the returns of other strategies. In this regard, the scale of production is particularly important, and the one whose effects on innovation have been studied most thoroughly. We therefore adopt the view that firms decide how much to produce and whether they should innovate or not simultaneously. The scale of production is commonly used as an explanatory variable of innovation activities in order to evaluate whether larger firms have an advantage over small ones in developing and adopting innovations, and thus support or refute the Schumpeterian hypothesis. However, the optimal scale of production may change with the adoption of innovations. This issue has far more important consequences than just dealing with the potential endogeneity bias of treating the scale of production as exogenous. [4] The recent work of Holmes, Levine, and Schmitz (2008) identifies precisely this simultaneity to argue that monopolistic firms have a lower incentive of adopting innovations than competitive ones. The reason, according to these authors, is that adopting a process innovation requires a temporary scale reduction —what they call "switchover disruptions"— and since monopolies forego larger rents by adopting cost reducing innovations than competitive firms, they also tend to postpone such innovation decisions much longer.

There may be complementarities among scale and innovation strategies. The existence of these complementarities offers several ways in which a more competitive environment may result in more innovation: competition may directly affect the returns to innovate, or alternatively competition may lead to a change in the optimal scale of production which triggers more innovation. We identify complementarities by assuming that firms maximize profits by choosing all relevant strategies simultaneously. The profit function is possibly supermodular and we impose minimum functional form assumptions in order to accommodate discrete strategies such as product and process innovation. This "functional form free" modeling approach vindicated by Vives (2008) aims to avoid misspecification due to restrictive functional form assumptions that cannot accommodate certain innovation patterns. Our equilibrium approach also allows for the existence of unobserved

[4] Cohen and Klepper (1996) consider the theoretical relationship between firm size and type of innovation in a framework plagued with functional form assumptions that drive many of the testable implications. However, the scale is treated as an exogenous variable in their econometric specification.

heterogeneity in the form of unobserved returns to the firms' strategies, which may be be correlated with each other. We then derive the optimal scale and innovation strategies from the profit function and employ an equilibrium approach. We do this in the sense that conditional on observable firm and market characteristics, the estimated parameters are those that maximize the likelihood that firms maximize profits by choosing their actual scale and innovation profiles.

In this paper we want to evaluate the impact that competitive pressure has on innovations of different kinds and identify how the effect is transmitted. Syverson (2004) suggests using the population density as a measure of how competitive markets are. More densely populated areas require more firms to serve it, thus facilitating consumers to switch suppliers and therefore leading to larger degree of product substitution. According to Vives (2008, §1), this is a proper measure of competitive pressure both with and without entry. The effect of population density identifies competitive pressure in our application through variations across markets and time in the case of industry density. A major advantage of our study is that we benefit from a natural experiment to obtain an alternative measure of increased competitive pressure. Specifically, we observe an exogenous shift in the regulation of the automobile distribution system in Europe that facilitates entry and more aggressive commercial practices in the automobile dealership industry after 2002. We argue that such liberalization affects how competitive the market for dealers is, which in turn increases or reduces the incentive to innovate.[5]

The rest of the paper is organized as follows. Section 2 briefly reviews the institutional details of the European automobile distribution system and its liberalization in September 2002. This section also describes the innovation decisions that we consider and presents preliminary evidence on the existence of complementarities. Section 3 builds the econometric model and discusses its coherence by showing that the model leads to a unique value for the choice variables for any given value of the observed and unobserved firm and market characteristics. Section 4 reports the estimates of different specifications, some of them allowing for complementarity among strategies to be driven by unobserved heterogeneity, some of them restricting such relationships to depend only on observable firm and market characteristics. This allows us to conduct various specification tests and evaluate the estimation bias of an increase in competitive pressure (and other variables) if complementarity relationships were to be ignored. We also evaluate the direct and indirect effects of liberalization on all strategies simultaneously by simulating firms profiles and evaluating them at the parameter estimates and firm and market characteristics in our sample.

[5] The direct effect of antitrust regulation on innovation is largely an unexplored area. An exception is the work of Segal and Whinston (2007) who consider how more or less protective policies toward entrants affect the overall innovation in a model with successive generations entrants who turn into incumbents and of incumbents who eventually leave the industry.

Section 5 concludes. The full derivation of the likelihood function assuming that structural errors follow an unrestricted multivariate normal distribution is relegated to Appendix A.

2 Data and Institutional Background

We study the French car dealership industry between 2000 and 2004. The change in regulation that occurred during this time period constitutes an interesting natural experiment that provides us with an unusual measure of increased competitive pressure. Specifically, our data include a substantial regime change in the vertical restrains allowed by the European Commission in the automobile distribution system. While this change of rules was largely anticipated, its specific implementation was not. We argue that forcing automobile manufacturers to opt between a selective dealership system and territorial exclusivity increases competition among dealers. This allows us to study how an increase in competitive pressure a□ects scale and di□erent innovation choices, both directly on their associated returns, and indirectly through the potential complementarities among these strategies. Our data contain firm specific information on the use of di□erent software as well as the associated profits of these firms. This allow us to identify the parameters of an equilibrium model of innovation behavior in the presence of complementarities among firms' strategies.

This section first provides a quick overview of the liberalization of the automobile distribution system in Europe and argues that relaxing entry barriers led to an increase in competitive pressure. We then describe the data sources and features of the endogenous variables of our model and present preliminary evidence in favor of complementarity and of a significant change of behavior after the liberalization of the automobile distribution system in 2002.

2.1 Liberalization of the European Automobile Distribution System

For years, the automobile industry defended that *selectivity* and *territorial exclusivity* were exempted from antitrust enforcement arguing that they jointly ensured necessary incentives for sales and after-sales services.[6] European authorities gave in repeatedly to the industry's demands. Regulation 123/85 permitted these two restrictions as a block exemption from EU competition rules. Regulation 123/85 was adopted in 1985 and expired in 1995. This exemption was unexpectedly renewed and followed in 1995 by a similar block exemption, Regulation 1475/95, which was set to expire in September 2002. As this second block exemption came to an end, it was decided that automobile manufacturers could only impose either selectivity or territorial exclusivity to their dealers, but not both, after September 2002.

[6] This subsection is based on Brenkers and Verboven (2006, §1-2,8) and Brenkers and Verboven (2008, §2.3).

Selectivity allows automobile manufacturers to select dealers by some arbitrary criteria such as minimum staff training, advertising, storage, and most importantly the obligation to provide after-sales repair and maintenance services. Selectivity restricts dealers to sell automobiles only to final consumers and not to non-authorized intermediaries or dealers outside the manufacturers' networks. *Territorial Exclusivity* refers to the manufacturers' right to appoint only one dealer in a given geographical area. Dealers are not allowed to own branches of their dealerships outside the exclusive territory and their advertising efforts should be primarily aimed at this specific market. Together, selectivity and territorial exclusivity reduce the total number of dealers. After 2002, most manufacturers (with the exception of Suzuki) chose to enforce selective vertical restraints only, which led dealers to open other domestic and foreign branches and to intensify competition across markets.[7]

How does the removal of any of these restrictions enhance competition? They help promote competition by reducing international price differences of automobiles and inter-regional price differences in after-sales services. Dealers can open additional outlets in other domestic regions as well as abroad and trade those models that are relatively more profitable in each market. Similarly, unauthorized dealers could resell automobiles and be able to offer original spare parts and services without the consent of manufacturers. In equilibrium this reduces the ability to charge different markups in different markets.[8] Additionally, dealers carrying the same brand of automobiles may now compete more fiercely for customers in other areas or through independent resellers. Thus, the intensified intrabrand competition helps eliminate the existing double marginalization and lowers final prices paid by consumers, as argued by Rey and Stiglitz (1995). In addition, some of the other liberalizing measures adopted after 2002 allowed dealers to sell automobiles from different manufacturers and most importantly, to relax the need to offer after-sales services. Finally, both authorized and independent after-sales services were given the right to purchase original spare parts or spare parts of matching quality from independent manufacturers, further increasing competition that dealers face.

Is this change in regulation a good proxy for the increase in competitive pressure among European dealers? Expiration of Regulation 1475/95 was largely predictable. However, there were talks of extending the previous exemption further and manufacturers lobbied for their preferred forms of regulation. Thus, the particular features of the 2002 liberalization proposals were not completely anticipated, and certainly they have little to do with the innovation proneness of auto-

[7] Suzuki dealers otherwise became free to sell to independent resellers that are not necessarily in the manufacturers' networks.

[8] Goldberg and Verboven (2001) and Verboven (1996) document the use of price discrimination in the automobile industry across European markets.

Table 1: Sample Distributions of Endogenous Variables

	All periods		Before		After	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
x_d	0.066	0.248	0.076	0.266	0.046	0.209
x_c	0.171	0.376	0.160	0.367	0.192	0.395
x_y	3.09	1.67	2.99	1.70	3.28	1.59
π_i	18.10	97.10	18.40	98.00	17.45	95.70
N	639		420		219	

Means and standard deviations of endogenous variables by competition regime. Innovation indicators are dummy variables. Scale is measured in logarithm of thousands of euros while profits are measured in thousands of euros. N denotes the number of dealers in each sample.

mobile retailers. Furthermore, the increase in competitive pressure exclusively affects the ability of retailers to secure their monopoly rents. As Gilbert (2006, §III) recommends, the regime shift does not affect other determinants of innovations such as technological opportunity or appropriability. We will thus identify years 2003 and 2004 (LIB dummy variable) as those where competition is more intense after the liberalization of the European automobile distribution system.

2.2 IT Innovations in Automobile Retailing

Our data include innovation strategies, sales, and profits of the *Motor Vehicle Dealers* industry in France (SIC code 5511) from 2000 to 2004. We focus on the French market because data is quite complete, collected with a consistent methodology, and available for a large number of well defined submarkets. French *dèpartements* define areas with fairly homogeneous markets conditions. In addition, the large number of *dèpartements* (about a hundred) allows our econometric analysis to benefit from significant regional diversity. Table 1 presents basic descriptive statistics of the four endogenous variables of this study: product innovation ($x_{d\,i}$); process innovation ($x_{c\,i}$); scale ($x_{y\,i}$); and profits, (π_i).

The data set we use is built from a large firm-level database on the usage of Information and Communication Technologies (ICT). Specifically, the data contain yearly information on the software utilization of about 4,000 companies in a wide variety of industries. We merge the software data with other data sets including firm specific accounting information, as well as socioeconomic and demographic data from publicly available sources. We now describe these data sources more in detail and discuss how each innovation indicator can be interpreted as demand enhancing or cost reducing innovation.

1. ICT data is collected by Harte-Hanks (HH), a worldwide direct marketing company providing information on computer, software and IT staff usage to clients such as IBM and Oracle for their direct marketing purposes. The data is collected by European and US based call centers. The commercial purpose of this data ensures a high level of accuracy as users would quickly discover if HH's numbers were incorrect when their salesmen made a sales call. Data include numbers of PCs, servers, and mainframes, the size of the IT department and its functions, as well as brand, version, and usage of specific software. The data is provided annually per site ($i.e.$, for each address). In our empirical setting, most of the firms have only one site so we treat sites and firms as equivalent. Further, we believe that this is justified since decisions about the introduction of specific software programs (as will be specified below) is likely to take place at the site rather than the corporate level.

2. The data set $AMADEUS$ contains the financial accounts of a large number of companies registered in France. One of the key advantages of using $AMADEUS$ is that it contains data on listed as well as unlisted companies. This is particularly useful because it also allows us to study the adoption behavior of small and medium sized firms and not only large ones. Reporting regulations in France ensure that we have access to a large amount of financial information, including turnover, employees, tangible assets, costs, and profits.

3. French socioeconomic and demographic data is available from the French Statistical Office ($INSEE$). We collect $d\grave{e}partement$ level data on gross domestic product (GDP) and the ln($Population$) to proxy for market size. We also collected the surface of these $d\grave{e}partements$ in order to obtain a measure of population density for these markets. Furthermore, we identified those $d\grave{e}partements$ containing large cities (Paris, Marseille, Lyon, Toulouse, and Nice all exceed 300,000 inhabitants).

We identify two applications that proxy for demand enhancing and cost reducing innovations to study the transmission channel of an increase in competitive pressure on the different types of innovations. We study the adoption of two software packages, specifically human resource management software hr, and applications development software apps, respectively.

hr management software refers to the range of software applications that regulate all the personnel related data flow, such as tracking employees' participation in benefits programs, administering the recruiting process, and implementing human resource practices more efficiently. In essence, hr software is used to support human resource processes that were previously administered manually facilitating savings on administrative expenses, especially personnel. Operating

Table 2: Distribution of Innovation Profiles

	All periods			Before			After		
	%	$\overline{x}_y$	$\overline{\pi}$	%	$\overline{x}_y$	$\overline{\pi}_i$	%	$\overline{x}_y$	$\overline{\pi}$
None	77.2	2.99	20.1	77.1	2.88	20.6	77.2	3.19	19.0
Only Product	5.8	3.44	5.0	6.9	3.37	5.2	3.7	3.70	4.1
Only Process	16.3	3.34	10.8	15.2	3.24	11.3	18.3	3.48	9.9
Both	0.8	5.54	74.9	0.7	5.62	64.9	0.9	5.41	90.0

Percentage of firms adopting every possible combination of innovations. Scale is measured in logarithm of thousands of euros while profits are measured in thousands of euros.

costs of hr management software adopters are, *ceteris paribus*, likely to be lower than those of non-adopters.[9] Thus hr accounts for process innovation x_{ci} in our model.

apps development software grew out of programming languages such as C++, Basic, or Fortran and contains added functionality like debugging or requirements testing to facilitate the development of own, customized software applications. Thus, apps effectively provides a user interface and toolbox for programmers.[10] Applications are highly industry-specific, highly specialized, and often support mass customization like "car configurators" (web based software where potential buyers can customize their desired automobile) or specialized software components that enter the end product. Typically, apps facilitates applications development where no ready-made applications exist or where its customization would be too expensive. Since ready-made applications dominate the market for improving the efficiency of standard business processes (like HR management), and customizable products like like *SAP ERP* (an enterprise resource planning system that supports typical functions in an organization such as finance, controlling, materials, and sales), regulates industry-specific material and information flows across different processes within the firm, it seems plausible that apps software will most commonly be used to develop fully customized applications for tasks that add value to the product or service sold. These are sources of differentiation among firms and are therefore both (i) firm-specific and (ii) unlikely to be outsourced to third parties. We thus believe that firms adopt application development software for revenue-enhancing reasons so that apps accounts for product innovation x_{di} in our model.

Firms decide on the scale of production x_{yi}, measured as the logarithm of turnover in thousands of euros, together with the adoption of a demand enhancing innovation x_{di}, and the

[9] Is seems reasonable to assume that the cost reduction is proportional to the number of employees in the firm, given many hr processes take place *per employee*.

[10] The most prominent examples of application development software are Microsoft's *Visual Basic* at the low end and Borland's *Delphi* at the high end.

adoption of a cost reducing innovation x_{ci}.[11] The choice of these strategies together with others that we do not observe determines the level of profits for each firm π_i. We measure profits as turnover minus remuneration and materials cost (again in thousands of euros). Unlike many other studies, our empirical analysis treats the scale of production as an endogenous variable. Is there any evidence that the scale varies with the set of innovations adopted? Table 2 breaks down the distribution of innovation profiles by type of firm and across competition regimes. For each innovation profile the average scale and profits of the corresponding subsample of firms are also reported. Most dealers do not engage in any innovation strategy, but there is an overall change in innovation strategies after the liberalization of the European automobile distribution system. Dealers narrow the scope of their innovation profiles by further favoring process over product innovations. Finally, substantially larger dealers are more likely to engage in joint adoption of innovations. Therefore, a model where the scale of production was treated as exogenous would be misspecified in the present case.

3 Econometric Model

The estimation approach of this paper fully implements the framework put forward by Athey and Stern (1998). This is the first time that the *adoption approach* (based on innovation profiles of firms) and the *productivity approach* (based on the actual return of each strategy) are integrated in a single estimation procedure.[12] The estimation makes use of the information on profits associated with each scale decision and innovation profile of each firm. This introduces several restrictions on unobservables that are sufficient to produce meaningful estimates that control for unobserved heterogeneity. [13] Innovation indicators are dummy variables, which adds to the complexity of the estimation, but accurately reflects the discrete nature of innovation decisions, especially their adoption. In addition, and to deal with the important effects of unobserved returns to each strategy, we assume them to be jointly normally distributed so that we can evaluate how the unobserved heterogeneity associated with implementing each strategy, —*i.e.*, unobserved, strategy specific returns— affects the profitability of the rest of the strategies. As Athey and Stern (1998, §4.2)

[11] Essentially, firms with market power or differentiated products will pick a point on their demand curve by choosing either prices or quantities, which leads to a corresponding level of revenues (scale in our specification) known to the firms.

[12] Athey and Stern (2002) and Ichniowski, Shaw, and Prennushi (1997) are examples of the productivity approach while Miravete and Pernías (2006) is an example of the adoption approach. Cassiman and Veugelers (2006) apply both approaches separately to study potential complementarities between internal R&D and external knowledge acquisition.

[13] Our econometric model extends Miravete and Pernías (2006) by relaxing all their restrictive identification assumptions since our data also include firms' profits in addition to the chosen scales and innovation profiles.

Table 3: Unconditional Complementarity: Association among Endogenous Variables

	x_y, x_d	x_y, x_c	x_d, x_c	π, x_y	π, x_d	π, x_c
All Years	0.112***	0.019	−0.036	0.789***	0.121***	0.028
Before	0.131***	0.022	−0.052	0.789***	0.138***	0.030
After	0.090	−0.007	0.005	0.785***	0.106*	0.005

Kendall's τ association coefficients. Significance levels are indicated with * for p-values less than 0.1; ** for less than 0.05; and *** for less than 0.01.

point out, allowing for an unrestricted variance-covariance matrix of the distribution of these unobserved returns *"provides a parsimonious specification that still accommodates the main alternative hypothesis regarding complementarity among strategies and the role of unobserved heterogeneity."*

Before proceeding with the description of the econometric model we consider if there is any need to address the existence of complementarities in our data. Is there any suspicion that our approach is needed to model the choice of strategies by the French automobile distribution firms? Table 3 reports Kendall's τ coefficients of association among the different strategies of firms and between each strategy and profits before and after the liberalization of the European automobile distribution system. These nonlinear correlation coefficients are useful to test for the existence of unconditional complementarity, *i.e.*, the outcome of a profit function being pairwise supermodular in each possible pair of strategies while ignoring all other differences among firms.[14] Results show that larger firms are more likely to engage in demand enhancing innovations, especially before liberalization. Along the lines of the relations already discussed in Table 2, product and process innovations appear to be substitutes, *i.e.*, the profit function would be submodular in demand enhancing and cost reducing innovations, although this negative correlation is not significant. Notice however that correlations of Table 3 ignore any source of (observable or unobservable) heterogeneity. The following econometric model allows us to disentangle these two sources of heterogeneity and test whether complementary relationships play any (significant) role in the transmission of the effects of competitive pressure on innovation activity.

3.1 The Profit Function

We write the profit function of firm i as

$$\begin{aligned}\pi_i(x_{d\,i}, x_{c\,i}, x_{y\,i}) = \theta_\pi + \epsilon_{\pi\,i} + (\theta_d + \epsilon_{d\,i})x_{d\,i} + (\theta_c + \epsilon_{c\,i})x_{c\,i} + (\theta_y + \epsilon_{y\,i})x_{y\,i} + \\ \delta_{dc}x_{d\,i}x_{c\,i} + \delta_{dy}x_{d\,i}x_{y\,i} + \delta_{cy}x_{c\,i}x_{y\,i} - (\gamma/2)x_{y\,i}^2.\end{aligned} \tag{1}$$

[14] Arora and Gambardella (1990) first computed similar correlations to test for the existence of complementarity although the theoretical foundation of this test is due to Holmström and Milgrom (1994).

This is a general approximation to the profit function which imposes very little structure on the underlying production technology. It is quadratic in scale $x_{y\,i}$ and adoption of innovations is represented by two dichotomous variables, $x_{d\,i}$ and $x_{c\,i}$. It also includes interaction terms among all these strategies —parameters δ_{dc}, δ_{dy}, and δ_{cy}— whose estimated signs determine whether the profit function is supermodular or submodular in each pair of strategies. No assumptions are made about these potentially complementary relations and our estimates will determine them regardless of whether the strategies are continuous, such as the scale, or discrete, as in the case of innovations. We envision firm i choosing its scale and innovation profile in order to maximize the profit function $\pi_i(x_{d\,i}, x_{c\,i}, x_{y\,i})$. For the solution of this problem to be well defined we only need to assume that equation (1) is concave on the $x_{y\,i}$ dimension.[15]

An important goal of the econometric estimation is to determine whether the association results of Table 3 are due to the existence of complementarities, *i.e.*, estimates of δ_{dc}, δ_{dy}, or δ_{cy} that are significantly different from zero, or alternatively, that the correlations are due to the existence of other observed or unobserved elements of the environment of the firm for which we do not have information. The existence of returns $(\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i})$ that are observed by firms but not by econometricians explains why firms with identical observable characteristics $(\theta_d, \theta_c, \theta_y, \theta_\pi)$ may end up choosing different strategies $(x_{d\,i}, x_{c\,i}, x_{y\,i})$ and reaching different profit levels, π_i. For this reason the return of each strategy, *i.e.*, its direct impact on profits, includes an observed component —θ_d, θ_c, and θ_y— and an unobserved one —$\epsilon_{d\,i}$, $\epsilon_{c\,i}$, and $\epsilon_{y\,i}$—to control for the possibility that unobservable features of firm organization[16] and/or the innovation and production decisions lead to co-movements among strategies that are only the result of not having more detailed information about the relevant environment in which firms operate. Note also that there is an independent contribution to profits from other activities of the firm. This separate profit contribution of other strategies also distinguishes between an observed component, θ_π and an unobserved one, $\epsilon_{\pi\,i}$. They will be allowed to be correlated with the rest of unobserved returns of the model.[17]

The rest of this section discusses how the available information suffices to identify the key parameters of the model. We show that for any vector $(\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i})$ of unobserved returns to

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[15] See Athey and Schmutzler (1995) for demand and cost conditions leading to a supermodular profit function in a model similar to (1).

[16] These could be, for example, the flatness of the firm's hierarchy Bresnahan, Brynjolfsson, and Hitt (2002) or firm strategy Mahr and Kretschmer (2008).

[17] The stochastic structure of equation (1) is what Athey and Stern (1998) label "Random Practice Model," *i.e.*, a profit function where each strategy incorporates an unobservable return. While the elements of $(\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i})$ will be allowed to be correlated with each other, any one of them does not depend on the adoption of other practices. Thus, parameters affecting the cross-products of strategies $(\delta_{dc}, \delta_{dy}, \delta_{cy})$, are non-stochastic as in the "Random System Model" where each combination of strategies might have a common unobserved return. The model would no longer be identified if we included these additional stochastic components in the complementarity parameters without additional observable firm characteristics associated to each joint combination of strategies.

demand enhancing and cost reducing innovations, unobserved returns to production scale, and the profit contribution of the rest of strategies, respectively, there is a unique vector $(x_{d\,i}, x_{c\,i}, x_{y\,i}, \pi_i)$ of optimal strategies and total profits that rationalizes the observed scale and innovation profile as profit maximizing behavior. We also derive the restrictions on the unobservables of the model implied by profit maximizing behavior. These conditions will play an important role in our estimation procedure, that is sketched at the end of the section.

3.2 Scale choice

We first analyze the optimal scale choice. The first order condition for profit maximization is

$$\frac{\partial \pi_i}{\partial x_{y\,i}} = \theta_y + \epsilon_{y\,i} + \delta_{dy} x_{d\,i} + \delta_{cy} x_{c\,i} - \gamma x_{y\,i} = 0. \tag{2}$$

From here, the optimal scale choice contingent on the innovation profile of the firm is

$$x_{y\,i}(x_{d\,i}, x_{c\,i}) = \gamma^{-1}(\theta_y + \epsilon_{y\,i} + \delta_{dy} x_{d\,i} + \delta_{cy} x_{c\,i}). \tag{3}$$

The su□cient condition for profit maximization requires that $\gamma > 0$, $i.e.$, that profit function (1) is concave in $x_{y\,i}$. Next, we write $\pi_i\,(x_{d\,i}, x_{c\,i}) = \pi_i(x_{d\,i}, x_{c\,i}, x_{y\,i}(x_{d\,i}, x_{c\,i}))$ and after substituting the optimal scale (3) into the profit function (1) we get

$$\pi_i\,(x_{d\,i}, x_{c\,i}) = \kappa_{\pi\,i} + \epsilon_{\pi\,i} + (\kappa_{d\,i} + \epsilon_{d\,i}) x_{d\,i} + (\kappa_{c\,i} + \epsilon_{c\,i}) x_{c\,i} + \delta x_{d\,i} x_{c\,i}, \tag{4}$$

where

$$\kappa_{\pi\,i} = \theta_\pi + (\theta_y + \epsilon_{y\,i})^2/(2\gamma), \tag{5a}$$

$$\kappa_{d\,i} = \theta_d + \delta_{dy}\big[\delta_{dy}/2 + (\theta_y + \epsilon_{y\,i})\big]/\gamma, \tag{5b}$$

$$\kappa_{c\,i} = \theta_c + \delta_{cy}\big[\delta_{cy}/2 + (\theta_y + \epsilon_{y\,i})\big]/\gamma, \tag{5c}$$

$$\delta = \delta_{dc} + \delta_{dy}\delta_{cy}/\gamma. \tag{5d}$$

3.3 Innovation profile choice

Once we have obtained the optimal scale as a function of innovations in equation (3), we now need to determine how the observed innovation profile identifies the innovation related parameters of the model. Firm i chooses its innovation profile to maximize profits. In our model, firms can adopt a demand enhancing innovation, in which case the binary indicator is $x_{d\,i} = 1$. Similarly,

when they adopt a cost reducing innovation, $x_{c\,i}$ = 1. Therefore, firm i chooses one out of four innovation profiles: (i) adoption of the demand enhancing innovation only, $x_{d\,i} = 1, x_{c\,i} = 0$; ($ii$) adoption of the cost reducing innovation only, $x_{d\,i} = 0, x_{c\,i} = 1$; ($iii$) adoption of both innovations, $x_{d\,i} = 1, x_{c\,i} = 1$; and ($iv$) adoption of no innovation at all, $x_{d\,i} = 0, x_{c\,i} = 0$. From equation (4), we can then write the profits for each of the four innovation profiles as follows:

$$\pi\ (1,1) = \kappa_{\pi\,i} + \kappa_{d\,i} + \kappa_{c\,i} + \delta + \epsilon_{\pi\,i} + \epsilon_{d\,i} + \epsilon_{c\,i}, \tag{6a}$$

$$\pi\ (1,0) = \kappa_{\pi\,i} + \kappa_{d\,i} + \epsilon_{\pi\,i} + \epsilon_{d\,i}, \tag{6b}$$

$$\pi\ (0,1) = \kappa_{\pi\,i} + \kappa_{c\,i} + \epsilon_{\pi\,i} + \epsilon_{c\,i}, \tag{6c}$$

$$\pi\ (0,0) = \kappa_{\pi\,i} + \epsilon_{\pi\,i}. \tag{6d}$$

These expressions provide us with the restrictions on unobservables associated with each innovation profile. Thus, for instance, a firm engages in both innovation activities if the following three conditions are fulfilled:

$$\pi\ (1,1) > \pi\ (1,0), \tag{7a}$$

$$\pi\ (1,1) > \pi\ (0,1), \tag{7b}$$

$$\pi\ (1,1) > \pi\ (0,0). \tag{7c}$$

These conditions imply that observing firm i adopting both innovations correspond to the following restrictions on the unobserved returns of product and process innovation $(\epsilon_{d\,i}, \epsilon_{c\,i})$:[18]

$$\epsilon_{d\,i} > -\kappa_{d\,i} - \delta, \tag{8a}$$

$$\epsilon_{c\,i} > -\kappa_{c\,i} - \delta, \tag{8b}$$

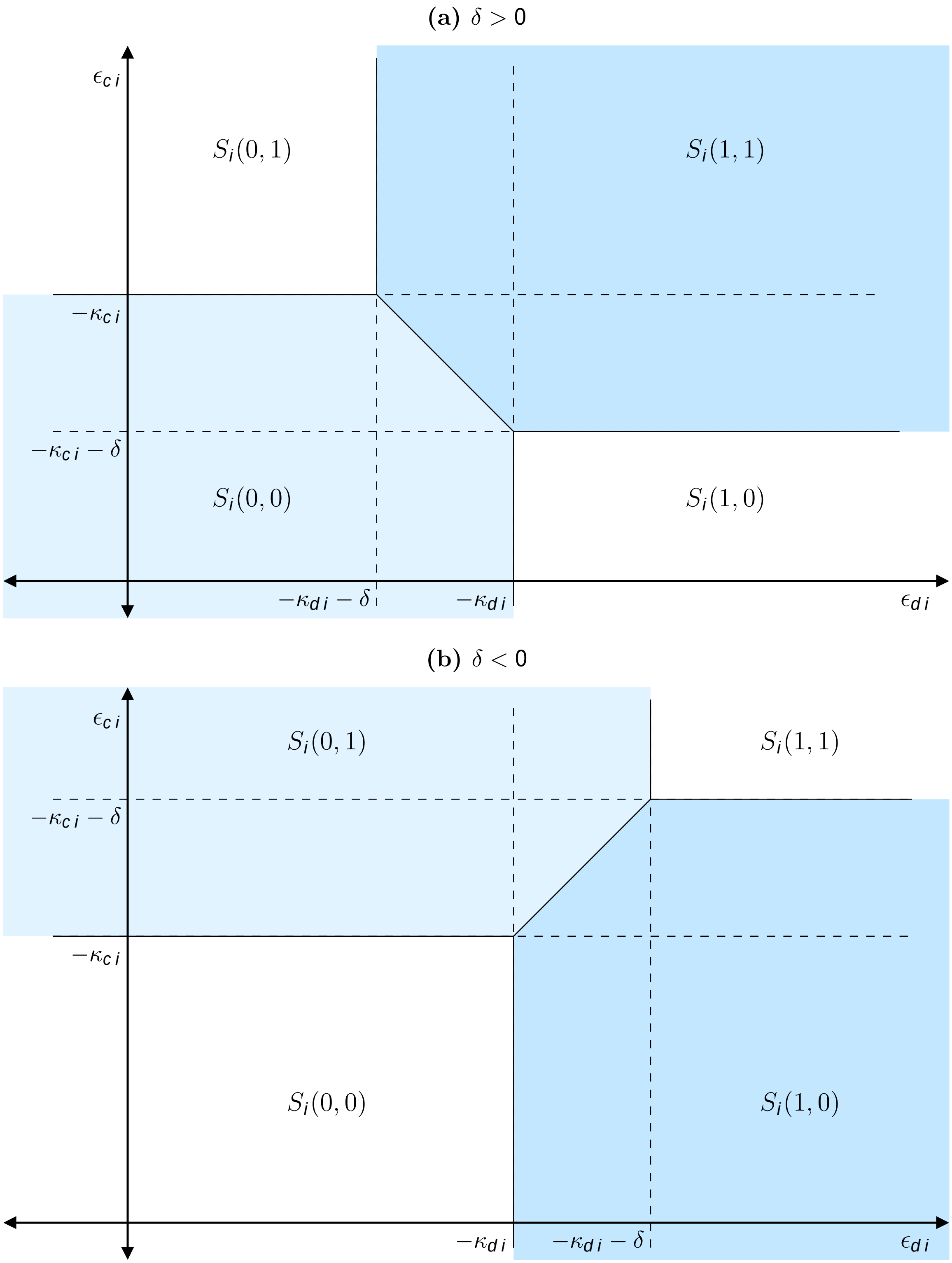
$$\epsilon_{d\,i} + \epsilon_{c\,i} > -\kappa_{d\,i} - \kappa_{c\,i} - \delta, \tag{8c}$$

We can repeat this analysis for all other innovation profiles. The following notation generalizes inequality conditions (8a)–(8c). Let $S_i(x_{d\,i}, x_{c\,i})$ denote the set of realizations of $(\epsilon_{d\,i}, \epsilon_{c\,i})$ for any given value of $\epsilon_{y\,i}$ such that they lead to the observed choices of product and process innovation,$(x_{d\,i}, x_{c\,i})$. The set $S_i(x_{d\,i}, x_{c\,i})$ is defined from the following three inequalities:[19]

[18] The third restriction (8c) is non-binding when $\delta \leq 0$, as can be checked by adding the first two conditions (8a) and (8b).

[19] As before, the last of these conditions is non-binding if $s_i\delta \leq 0$.

Figure 1: Innovation Profile Defining Regions



$$q_{d\,i}\epsilon_{d\,i} > -q_{d\,i}(\kappa_{d\,i} + \delta x_{c\,i}), \tag{9a}$$

$$q_{c\,i}\epsilon_{c\,i} > -q_{c\,i}(\kappa_{c\,i} + \delta x_{d\,i}), \tag{9b}$$

$$q_{c\,i}\epsilon_{s\,i} > -q_{c\,i}\big[\kappa_{c\,i} + \delta/2 + s_i(\kappa_{d\,i} + \delta/2)\big], \tag{9c}$$

To write these general inequalities, we made use of the following definitions:

$$\epsilon_{s\,i} = \epsilon_{c\,i} + s_i\epsilon_{d\,i}, \tag{10}$$

$$q_{d\,i} = 2x_{d\,i} - 1, \tag{11}$$

$$q_{c\,i} = 2x_{c\,i} - 1, \tag{12}$$

$$s_i = q_{d\,i}q_{c\,i}. \tag{13}$$

Figure 1 shows the shape of the $S_i(x_{d\,i}, x_{c\,i})$ regions for positive and negative values of δ. Notice that these disjoint regions are defined by the observed and unobserved return of profits associated to scale and innovations. Neither $\epsilon_{\pi\,i}$ nor θ_π appear in conditions (9a)–(9c). However, both $\epsilon_{y\,i}$ and θ_y define these integration regions through $\kappa_{d\,i}$ and $\kappa_{c\,i}$. Further, as long as the profit function is increasing and concave in $x_{y\,i}$, *i.e.*, $\gamma > 0$ the model is coherent in the sense that any given realization of the errors $(\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i})$ is associated unambiguously with a firm with given scale, innovation profile, and profit level.[20] The intuition of this identification result goes as follows. First, observe that each realization of $(\epsilon_{y\,i}, \epsilon_{d\,i}, \epsilon_{c\,i})$ is uniquely associated with a particular innovation profile $(x_{d\,i}, x_{c\,i})$ through conditions (9a)–(9c). Then, equation (3) uniquely determines the scale $x_{y\,i}$. Finally, for any given a realization of $\epsilon_{\pi\,i}$, the observable direct profit contribution of the rest of strategies θ_π, is determined by equation (1) as a residual from observable profits and the share accounted for by scale and innovations. Thus, for a given realization of $(\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i})$ there is a unique corresponding vector $(x_{d\,i}, x_{c\,i}, x_{y\,i}, \pi_i)$ that satisfies the profit maximization conditions for the parameters $(\theta_d, \theta_c, \theta_y, \theta_\pi)$.

[20] As Figure 1 points out, the areas of integration corresponding to each innovation profile are not rectangular unless $\delta = 0$. This situation is common in the entry literature. Both Berry (1992) and Mazzeo (2002) encounter non-rectangular integrations areas similar to those of Figure 1. They resort to simulation to estimate their models. Miravete and Pernías (2006) make use of a Gauss-Legendre quadrature to evaluate the probabilities of each innovation profile. Appendix A shows that a simple change of basis allows us to evaluate Prob $[(\epsilon_{d\,i}, \epsilon_{c\,i}) \in S_i(x_{d\,i}, x_{c\,i})]$ as the sum of two bivariate normal integrals over two disjoint regions. If we were to consider numerous discrete strategies this method would become impractical and we would also have to resort to simulations to estimate our model.

In order to estimate the model we assume that $\boldsymbol{\epsilon}_i = (\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i})'$ follows a tetravariate normal distribution with zero means and standard deviations $(\sigma_d, \sigma_c, \sigma_y, \sigma_\pi)'$. The joint density of $\boldsymbol{\epsilon}_i$ can be written as

$$f(\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i}) = (\sigma_d \sigma_c \sigma_y \sigma_\pi)^{-1} \phi_4 \left(\frac{\epsilon_{d\,i}}{\sigma_d}, \frac{\epsilon_{c\,i}}{\sigma_c}, \frac{\epsilon_{y\,i}}{\sigma_y}, \frac{\epsilon_{\pi\,i}}{\sigma_\pi}; \boldsymbol{R} \right), \tag{14}$$

where $\phi_4(\cdot; \boldsymbol{R})$ denotes the probability density function of a four-variate normal distribution with mean vector $\mathbf{0}$, unit variances, and correlation matrix

$$\boldsymbol{R} = \begin{pmatrix} 1 & \rho_{dc} & \rho_{dy} & \rho_{d\pi} \\ \rho_{dc} & 1 & \rho_{cy} & \rho_{c\pi} \\ \rho_{dy} & \rho_{cy} & 1 & \rho_{y\pi} \\ \rho_{d\pi} & \rho_{c\pi} & \rho_{y\pi} & 1 \end{pmatrix}. \tag{15}$$

Equation (3), and conditions (9a)–(9c), can be used to test for the existence and direction of complementarities, as in Miravete and Pernías (2006). But these conditions do not suffice for estimating all the parameters of the model. Observing profits enables us to estimate all parameters of the profit function (1) and the parameters driving the multivariate distribution of unobservables. Working along these lines, we construct the likelihood function of this model under the assumption that $(\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i})$ follows this unrestricted multivariate normal distribution in Appendix A.

4 How Does Competition Favor Innovation?

We now evaluate the effect of the different firm and market characteristics on the direct returns of each strategy. In doing so, we consider different specifications of the model allowing for alternative combinations of complementarities and unobserved heterogeneity. We specify the vector of parameters $(\theta_d, \theta_c, \theta_y, \theta_\pi)$ as linear functions of observable variables. As these four observable returns are identified independently we do not need to exclude regressors from any of these specifications to carry out the estimation. This is a welcome feature of the model because we do not have any *a priori* assumptions about the effect that any given regressor, say the population density, may have on the returns to innovate or to expand production. These returns are precisely what we want to evaluate by estimating the model.

Table 4 presents the sample distribution by competitive regime of all regressors we considered. However, not all of them are included in the final specification of the model reported in Table 6. Ideally we would like to include market and time fixed effects as regressors in the four

Table 4: Sample Distributions of Exogenous Variables

	All periods		Before		After	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
ln($GDPpc$)	3.195	0.320	3.172	0.325	3.240	0.305
ln($Density$)	5.541	1.767	5.530	1.755	5.563	1.791
ln($Population$)	13.596	0.674	13.583	0.672	13.622	0.679
$Urban$	0.106	0.309	0.093	0.291	0.132	0.340
$Near$	0.199	0.399	0.193	0.395	0.210	0.408
N	639		420		219	

Means and standard deviations of exogenous variables by competition regime. The first three variables are measured in logarithms. Gross domestic product per capita is measured in thousands of euros; population density in people per square kilometer; and population in number of inhabitants of each market. The remaining variables are dummies. N denotes the number of dealers in each sample.

observable returns $(\theta_d, \theta_c, \theta_y, \theta_\pi)$. However, this would leave us without sufficient observations given the large number of *dèpartements* and the many parameters of our nonlinear model. Our preferred model therefore only includes the following regressors:

1. ln($GDPpc$) is the logarithm of the gross domestic product per capita of each *dèpartement* measured in thousands of euros. We use this to account for differences of purchasing power of potential customers across markets that may reflect price elasticity of demand in each local market.

2. LIB is the dummy variable that identifies all observations from years 2003 and 2004, *i.e.*, once the European automobile distribution system was liberalized. This variable is intended to capture the effects of such a regime change and the associated increase in competitive pressure on all endogenous variables of the model.

3. ln($Density$) is the logarithm of the population density of each market measured as the number of people per square kilometer. Density may have several possible effects. First, density is related to the cost of storage and car display. If this effect dominates, this variable should affect scale negatively. Second, we could think of dense markets as being more competitive since consumers can compare prices, products, and quality of services more easily and thus switch from one dealer to another. Syverson (2004) argues that the pro-competitive effect of density is to foster efficiency (innovation in our case) and larger scales for a larger number of firms as smaller and less efficient ones do not survive in such demanding environments.

4.1 The Effect of Competitive Pressure on Innovation and Scale

Table 5 evaluates the effect of liberalization in the European automobile distribution system while ignoring the effect of any other regressor. Table 6 presents the estimates of four different specifications of the general model described in Section 3. The inclusion of market characteristics improves the estimation. Estimates of the liberalization effect (the estimate of LIB) are of the same sign and significance while estimates of complementarity effects, $(\delta_{dc}, \delta_{dy}, \delta_{cy})$ are remarkably robust to the inclusion of additional regressors. The same can be said about the correlation among the unobservable returns of each strategy, in particular for the results of Model IV.

Model I assumes away any complementarities among strategies and also ignores the existence of unobserved heterogeneity by assuming that unobserved returns are uncorrelated. The likelihood ratio test of Table 7 rejects Model I in favor of any of the other three specifications. Model II allows for the possibility of complementarities among strategies but still rules out the possibility that unobservable firm and market characteristics may lead to correlated strategies. Model II is also rejected in favor of either Model III or Model IV, indicating that the included regressors are unable to completely explain the the co-variation of endogenous strategies. Model III assumes that this co-movement is exclusively explained by unobserved factors and not by complementarities. Again, this specification is rejected in favor of the most general one, Model IV which allows for correlation among strategies to be explained both by unobservable returns and complementarities. That is, both unobservable heterogeneity and complementarities matter in explaining simultaneous scale and product and process innovation decisions. Therefore, estimates of Model IV offer the most reliable description of the effect of an increase in competitive pressure on each strategy. We will therefore concentrate on the parameter estimates of Model IV.

We start by analyzing the effect of market pressure. The liberalization of the European distribution system does not have any significant direct effect on the returns to either product or process innovation. Ignoring for the moment the cross-market differences in competitive pressure due to population density, how can this result be reconciled with the unconditional correlations in Table 3? One possibility that the present model allows us to consider is that the effects of an increase of competitive pressure on innovation are not direct but rather indirect through the change in the scale of production. Observe the positive sign of the estimate of LIB on the scale. This implies that a more competitive environment increases the optimal scale of dealerships. A larger scale in turn increases the profitability of adopting a demand enhancing innovation since these two strategies are complements, $i.e.$, $\delta_{dy} > 0$. Similarly, the adoption of product innovation reduces the profitability of process innovation as $\delta_{dc} < 0$. Product and process innovations are substitutes and firms specialize in adopting one or the other.

Table 5: Estimates: French Automobile Retailing (without Market Controls)

		Model I		Model II		Model III		Model IV	
θ_d	*Constant*	-15.79	(21.40)	-24.75	(22.29)	-23.35	$(11.04)^{**}$	-51.30	$(12.54)^{***}$
	LIB	-2.83	(4.28)	-5.00	(5.31)	-3.71	(3.18)	-7.87	(13.08)
θ_c	*Constant*	-5.48	(11.49)	-6.48	(9.38)	-29.05	$(7.37)^{***}$	-21.86	$(7.03)^{***}$
	LIB	0.69	(1.60)	0.65	(1.28)	7.94	(10.75)	4.99	(10.98)
θ_y	*Constant*	-3.69	$(1.13)^{***}$	-3.92	$(1.14)^{***}$	-1.51	$(0.49)^{***}$	-2.37	$(0.50)^{***}$
	LIB	3.97	$(1.88)^{**}$	4.02	$(1.88)^{**}$	1.63	$(0.79)^{**}$	1.91	$(0.77)^{**}$
θ_π	*Constant*	-2.21	(4.73)	-2.52	(4.66)	-4.88	(5.14)	-13.33	$(5.36)^{**}$
	LIB	2.05	(7.33)	2.13	(7.26)	-2.50	(8.30)	1.25	(8.70)
γ		13.41	$(1.08)^{***}$	13.43	$(1.08)^{***}$	5.49	$(0.75)^{***}$	5.43	$(0.43)^{***}$
σ_d		11.03	(14.93)	17.44	(15.56)	16.29	$(7.61)^{**}$	142.15	$(8.74)^{***}$
σ_c		5.50	(11.51)	6.68	(9.60)	127.41	$(4.28)^{***}$	129.39	$(4.74)^{***}$
σ_y		22.24	$(1.90)^{***}$	22.22	$(1.90)^{***}$	9.11	$(1.27)^{***}$	9.10	$(0.76)^{***}$
σ_π		87.22	$(2.44)^{***}$	87.23	$(2.44)^{***}$	98.22	$(2.94)^{***}$	102.60	$(3.15)^{***}$
δ_{dc}				-1.48	(1.98)			-155.52	$(11.21)^{***}$
δ_{dy}				1.77	(1.37)			10.43	$(1.31)^{***}$
δ_{cy}				0.56	(0.73)			0.52	(0.69)
ρ_{dc}						0.132	(0.13)	0.945	$(0.01)^{***}$
ρ_{dy}						0.168	$(0.10)^{*}$	-0.484	$(0.04)^{***}$
ρ_{cy}						-0.247	$(0.04)^{***}$	-0.286	$(0.04)^{***}$
$\rho_{d\pi}$						-0.134	(0.14)	-0.985	$(0.01)^{***}$
$\rho_{c\pi}$						-0.972	$(0.01)^{***}$	-0.967	$(0.01)^{***}$
$\rho_{y\pi}$						0.463	$(0.04)^{***}$	0.510	$(0.03)^{***}$
$-\ln\mathcal{L}$		1023.0		1016.4		649.0		590.4	

Maximum likelihood estimates. Standard errors are reported in between parentheses. Significance levels are indicated with * for p-values less than 0.1; ** for less than 0.05; and *** for less than 0.01. There is a total of 639 observations.

Liberalization has no direct effect on innovation but rather an indirect effect the induced increase in the optimal scale of dealerships. Our results partially support Arrow's view that competitive markets give the right incentives for innovation to flourish although only for demand enhancing innovations. However, the effect of liberalization on product innovation is only indirect, through an increase in the optimal scale of dealerships and the complementary relationship between scale and product innovation. A possible interpretation is that in a more competitive environment firms maximize profits by increasing their scale in order to compensate the reduction in their markups. A larger scale increases the profitability of further increasing the quality of the product or service through engaging in product innovation. Similarly, our results also support Schumpeter's view that a monopolistic market favors innovation but only when we deal with cost reducing innovations, and again in an indirect manner through the complementary effects of other strategies. According to our results it could be argued that the ability to capture rents from a cost saving innovation induces monopolistic firms to adopt them since they invest in process innovation less frequently when the market becomes more competitive. Therefore, liberalizing the automobile distribution system works in opposite directions depending on the type of innovation considered.

Table 6: Estimates: French Automobile Retailing

		Model I		Model II		Model III		Model IV	
θ_d	*Constant*	19.94	(436.49)	22.88	(573.02)	33.38	(308.19)	217.70	(211.70)
	LIB	−1.24	(26.97)	−1.41	(34.93)	−2.00	(18.78)	−2.84	(13.19)
	ln(*GDPpc*)	3.61	(78.82)	3.24	(83.49)	5.87	(54.41)	−23.22	(33.49)
	ln(*Density*)	−0.19	(4.09)	−0.06	(2.18)	−0.31	(3.20)	12.55	(8.64)
	ln(*Population*)	−0.86	(18.89)	−1.25	(30.35)	−1.45	(13.68)	−31.31	(15.40)**
θ_c	*Constant*	−24.97	(62.64)	−18.47	(545.61)	−240.23	(721.11)	−173.39	(175.20)
	LIB	0.51	(1.35)	0.32	(9.55)	12.75	(16.83)	7.84	(11.00)
	ln(*GDPpc*)	−0.99	(2.73)	−1.04	(30.31)	−76.14	(123.85)	−47.78	(27.25)*
	ln(*Density*)	−0.26	(0.69)	−0.13	(4.09)	13.47	(26.28)	9.05	(6.68)
	ln(*Population*)	1.40	(3.52)	0.94	(27.95)	−11.00	(47.14)	−5.67	(12.21)
θ_y	*Constant*	−15.66	(29.48)	−15.91	(57.56)	−7.26	(26.10)	−15.87	(12.74)
	LIB	2.72	(1.87)	2.73	(2.83)	1.17	(0.93)	1.53	(0.80)*
	ln(*GDPpc*)	16.49	(4.74)***	16.40	(10.59)	7.15	(4.79)	5.73	(2.02)***
	ln(*Density*)	−3.57	(1.15)***	−3.56	(2.94)	−1.56	(0.83)*	−1.47	(0.49)***
	ln(*Population*)	6.87	(2.11)***	6.85	(4.86)	3.02	(1.52)**	3.17	(0.91)***
θ_π	*Constant*	−12.49	(123.67)	−13.55	(433.25)	147.96	(718.30)	49.81	(141.06)
	LIB	−2.32	(7.45)	−2.27	(15.34)	−4.16	(13.12)	−1.55	(8.78)
	ln(*GDPpc*)	56.85	(18.85)***	56.78	(83.74)	45.22	(125.23)	43.89	(21.55)**
	ln(*Density*)	−14.00	(4.38)***	−13.96	(18.95)	−7.93	(25.08)	−9.27	(5.30)*
	ln(*Population*)	22.11	(8.10)***	22.16	(32.00)	4.34	(44.00)	11.18	(9.80)
γ		13.50	(1.07)***	13.49	(1.36)***	5.84	(1.13)***	5.71	(0.46)***
σ_d		4.28	(93.24)	4.46	(110.80)	6.85	(64.58)	143.47	(8.63)***
σ_c		3.57	(8.95)	2.57	(75.49)	130.29	(6.29)***	127.54	(4.64)***
σ_y		21.97	(1.84)***	21.94	(2.44)***	9.51	(1.76)***	9.39	(0.79)***
σ_π		86.10	(2.42)***	86.11	(2.15)***	98.08	(3.70)***	101.98	(3.14)***
δ_{dc}				−0.40	(8.86)			−159.86	(10.80)***
δ_{dy}				0.55	(12.44)			10.15	(1.28)***
δ_{cy}				0.23	(6.31)			0.10	(0.68)
ρ_{dc}						0.107	(0.49)	0.954	(0.01)***
ρ_{dy}						0.217	(0.28)	−0.461	(0.04)***
ρ_{cy}						−0.236	(0.07)***	−0.272	(0.04)***
$\rho_{d\pi}$						−0.042	(0.72)	−0.989	(0.01)***
$\rho_{c\pi}$						−0.969	(0.01)***	−0.964	(0.01)***
$\rho_{y\pi}$						0.468	(0.07)***	0.506	(0.03)***
$-\ln\mathcal{L}$		994.0		987.7		622.7		570.0	

Maximum likelihood estimates. Standard errors are reported in between parentheses. Significance levels are indicated with * for p-values less than 0.1; ** for less than 0.05; and *** for less than 0.01. There is a total of 639 observations.

Other regressors also have significant effects on the different strategies of the firms. The return to adopting product innovations is larger in smaller markets while process innovation is favored in less affluent and dense markets. The negative effect of ln($Population$) is surprising although the overall effect on innovation is uncertain since ln($Population$) also induces an increase in the optimal scale of dealerships which, in turn, favor the adoption of product innovations. As for cost reducing innovations, it could be argued that less affluent markets do not leave much room for profiting by offering a differentiated high quality product or service and thus firms can only opt for reducing costs as their main way to compete.

The non-significant effect of density as a static measure of competition intensity on innovation of any kind does not support the argument put forward by Syverson (2004). Notice also that firms choose larger scales in wealthier markets but contrary to Syverson (2004) more dense markets do not include the largest dealers. This suggests that the effect of costly storage dominates in an industry where space for display is scarce in dense cities.

Notice also that unobserved returns of the different strategies are significantly correlated with each other, therefore emphasizing the need to control for the existence of unobservable heterogeneity when estimating the determinants of firm strategies that might be complementary to each other. By comparing Models II and IV we can assess the role of ignoring unobserved heterogeneity. Estimates of Model II ignore unobserved returns and offer a starkly different interpretation of the effect of liberalization on the French car dealer industry. If we were to believe that ln($GDPpc$), ln($Density$) and ln($Population$) fully explain all decisions of firms we would conclude that there are no complementarities among strategies and that the increase in competitive pressure does not have any significant effect on the scale of production or innovation activities. These results would furthermore contradict the unconditional correlations among strategies reported in Table 3.

Similarly, comparing Model III and IV lets us evaluate the estimation bias of ignoring complementarities. The estimates of $(\rho_{dc}, \rho_{dy}, \rho_{cy})$ in Model III are those commonly used to evaluate complementarities following Arora and Gambardella (1990), that is, measuring the correlation of residuals after regressing the adoption of strategies on observable firm and market characteristics only. The estimates of Model III depict a situation where product innovation would be independent of any other strategy and small firms would have an advantage in implementing process innovations. The estimates of $(\delta_{dc}, \delta_{dy}, \delta_{cy})$ in Model IV tell quite a different story, as discussed above. Furthermore, ignoring complementarities also affects the significance of many other estimates, and in particular liberalizing the European distribution system has no significant effect on any choice variable.

4.2 Robustness of Estimates

Estimates reported in Table 6 do not use all the market information available to us. Since the theory does not offer any guidance on which variables should be excluded from the specification of the returns associated to each strategy, we experimented with different combinations of regressors to obtain the best fit of the model. Table 7 presents a collection of specification tests. All tests favor the specification of Model IV in Table 6 over any alternative.

The top section of Table 7 presents a set of likelihood ratio tests comparing the different specifications of the profit function under the null hypothesis that the first model (of each compar-

Table 7: Some Specification Tests

	χ^2	d.f.	p-value
LR tests for model comparisons			
Model I vs. Model II	12.64	3	0.005
Model I vs. Model III	742.58	6	0.000
Model I vs. Model IV	848.06	9	0.000
Model II vs. Model III	729.94	3	0.000
Model II vs. Model IV	835.43	6	0.000
Model III vs. Model IV	105.48	3	0.000
Wald test for joint significance			
All covariates	37.12	16	0.002
LIB	6.20	4	0.184
ln($GDPpc$)	13.76	4	0.008
ln($Density$)	9.60	4	0.048
ln($Population$)	16.13	4	0.003
LR tests for additional regressors			
$Y2001$	0.88	4	0.928
$Y2002$	2.89	4	0.576
$Urban$	4.22	4	0.377
$Near$	1.54	4	0.819

ison) is the correct one. All tests favor the more general specification against the restrictive one. Model IV is the preferred specification, which includes the possibility of complementarities among strategies as well as correlated unobserved returns to each strategy.

The middle section of Table 7 evaluates whether the included regressors in our preferred specification are at all informative. These are Wald tests where the null hypothesis is that these regressors are not jointly significant. Thus, for instance we test whether ln($GDPpc$) can be excluded simultaneously in the specification of θ_d, θ_c, θ_y, and θ_π. The answer in most cases is no. ln($Density$) could almost be excluded from the four return equations at a 95% significance level. The exception however is LIB, the dummy variable that identifies the regime change. While this variable could be excluded from the specification of the four returns simultaneously we did not do that because it is significant on the return of the scale of production, θ_y. All the other excluded variables are neither jointly nor individually significant in the specification of any single return.

The bottom section of Table 7 confirms that the remaining variables do not improve the estimation. The logic for their potential inclusion is the following (although the described effect fails to be significant):

1. *Urban* indicates whether a large city (over 300,000 people) is located within the *dèpartement* defining the market. Cities may attract more sophisticated customers and skilled professionals. Thus, because of agglomeration effects, it is more likely in these areas to find the expertise to develop and implement innovations that improve the service or allow firms to provide such services more efficiently.

2. *Near* designates those *dèpartements* surrounding the *dèpartement* where a large city is located. This regressor is used to test whether this administrative division corresponds to a well defined market for the purposes of our study.

Variables $Y2001$ and $Y2002$ are of particular interest. They are dummies that identify observations from the years 2001 and 2002, just ahead of the liberalization of the European automobile distribution system. As we discussed in Section 2.1, the former regulation of this industry was known to expire in September of 2002. Thus, it could be argued that our definition of LIB does not capture the full effect of liberalization because dealers anticipated it. It is however well documented that while the overhaul of the old regulatory regime was known, the defining features of the new one were not decided until soon before it was put into place. We cannot reject the hypothesis that the estimates of $Y2001$ and $Y2002$ are not significant (either jointly or individually in each return equation). This result strongly supports our claim that LIB was not anticipated and that it identifies an exogenous regime change.

4.3 Quantifying the Effect of Liberalization

Estimates of Table 7 indicate only the direct effect of each regressor on the corresponding return of each strategy. Thus, we can conclude that increasing the returns of the scale triggered by a 1% increase of GDP per person is equivalent to the effect of a reduction of the population density of about 4%. Similarly, the positive effect of LIB on the return of the scale of production is roughly equivalent to a 2% increase of the market population.

These numbers are of limited practical importance because they do not account for the interdependencies of strategies in the profit function. What is the overall effect of liberalizing the European automobile distribution system on the endogenous variables of our model? In the end the change in the scale of production and/or innovation profiles of firms responds to a combination of direct effects of liberalization plus the synergies of complementary or substitute strategies. The answer to this question is therefore complex because of the nonlinear nature of our model and the interactions among parameters on the one hand, and the existence of correlated unobserved returns on the other.

Table 8: Simulation of the liberalization effect: distribution percentiles

	5%	25%	50%	75%	95%
Total Effects					
$x_{y\,i}$(%)	0.03	13.73	22.87	32.06	44.91
$x_{c\,i}$	−1.72	1.88	4.38	6.89	10.49
$x_{d\,i}$	−7.51	−4.38	−2.35	−0.31	2.82
π(1000€)	−5.09	−1.56	0.91	3.42	7.22
None	−7.67	−4.07	−1.72	0.63	3.91
Only product	−6.89	−4.23	−2.50	−0.94	1.41
Only process	−1.25	1.88	4.07	6.26	9.55
Both	−1.56	−0.47	0.16	0.94	2.19
Direct Effects					
$x_{y\,i}$(%)	3.02	17.23	26.94	36.45	50.43
$x_{c\,i}$	−3.44	0.00	2.35	4.85	8.45
$x_{d\,i}$	−6.42	−2.97	−0.63	1.41	4.85
π(1000€)	−3.72	−1.11	0.60	2.40	5.03
None	−7.51	−3.91	−1.56	0.78	4.23
Only product	−2.03	−1.25	−0.78	−0.31	0.31
Only process	−0.31	1.25	2.35	3.44	5.16
Both	−5.32	−2.19	0.00	2.19	5.63
Complementarities Effects					
$x_{y\,i}$(%)	−13.49	−7.69	−3.96	−0.49	4.86
$x_{c\,i}$	−1.72	0.47	1.88	3.44	5.79
$x_{d\,i}$	−5.16	−2.97	−1.56	−0.16	2.03
π(1000€)	−5.88	−2.14	0.37	2.81	6.27
None	−1.72	−0.78	−0.16	0.31	1.41
Only product	−5.48	−3.13	−1.72	−0.31	1.72
Only process	−1.88	0.16	1.72	3.29	5.63
Both	−3.76	−1.25	0.16	1.72	4.07

Empirical distribution of the direct, indirect, and total effects of 100,000 simulations. They measure the percent change in the scale before and after the liberalization. Profits are measured in euros. All other variables are changes in probabilities (×100).

To evaluate the impact of the increase in competitive pressure, we will use our sample of firms to carry out a simulation exercise based on the estimates of Model IV from Table 6. Taking the value of the estimated distributional parameters —$(\rho_{dc}, \rho_{dy}, \rho_{d\pi}, \rho_{cy}, \rho_{c\pi}, \rho_{y\pi})$ and $(\sigma_d, \sigma_c, \sigma_y, \sigma_\pi)$— of Model IV as given, we generate five thousand random draws of the rest of parameters of the model from their sampling distribution (given by the estimated coefficients and covariance matrix of estimates). For each of these five thousand draws we generate twenty draws of unobserved returns $(\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i})$, which are jointly distributed according to an multivariate normal distribution with expectation 0 and covariance matrix given by the estimates of the correlation coefficients $(\rho_{dc}, \rho_{dy}, \rho_{d\pi}, \rho_{cy}, \rho_{c\pi}, \rho_{y\pi})$ and standard deviations $(\sigma_d, \sigma_c, \sigma_y, \sigma_\pi)$ in Model IV of Table 6. We then compute the predicted choices of scale, product innovation, process innovation, and profit

realizations $(x_{d\,i}, x_{c\,i}, x_{y\,i}, \pi_i)$ for every firm before the liberalization, $i.e.$, when LIB = 0, for each of the one hundred thousand simulated scenarios. We then repeat the analysis adding the estimated value of LIB to the return of each strategy and recompute all optimal choices after the liberalization, $i.e.$, when LIB = 1. The difference indicates the overall effect that liberalization has on each element of interest of the model.

Table 8 presents the overall effect of the liberalization on the endogenous variables. Instead of averaging over the one hundred thousand simulations, Table 8 reports their empirical distribution by reporting the percentiles of the effect of liberalization on each variable of interest so that we can evaluate whether the sign of these simulations might be ambiguous. The range defined by the 5% and 95% percentiles is the 90% confidence interval of the empirical distribution of the effect of liberalization. We will focus our attention on the median effect as it it very similar to the average effect since the empirical distribution of simulations are quite symmetric.

Table 8 divides the total effects of liberalization between those derived under the assumption of independent strategies and those due to complementarity. The total effects are the result of evaluating exactly Model IV of Table 6. The effects under independence ignore any synergy due to complementarity; $i.e.$, we evaluate Model IV of Table 6 but restrict $\delta_{dc} = \delta_{dy} = \delta_{cy} = 0$. The effects due to complementarity are simply computed as the difference between the other two. Consider the case of profits as an example. The median increase in profits after the liberalization amounts to 910€ (profits are measured in thousand of euros in the table). The median direct effect of liberalization is only 600€ while median profit synergies due to complementarities amount to 370€. The increase in profits after liberalizing the European automobile distribution system is however not generalized while the bottom 5% of dealers lose at least 5,000€ and the top 5% increase their profits by more than $7,220$€.

Table 8 also reports the percent increase in the scale. Liberalization triggers a median increase of 23%. In this case the direct effect, 27%, exceeds the total effect because the increase in process innovation when scale and process innovation are substitutes leads to an indirect effect of scale reduction of about 4%. The reduction in product innovation when scale and product innovation are complements play in the same direction. Ignoring complementarities would have thus lead to an important overestimation of the effect of liberalization on the scale. The increase in the scale is the only unambiguous effect of liberalization: the 90% confidence interval of simulations ranges between a 0.03% and a 44.91% increase in the scale.

Finally, as for the innovation strategies, we report the change in probabilities ($\times$100) of being adopted before and after the liberalization. The overall effect of liberalization on the adoption of product and process innovation is to increase the adoption of proccess innovation and reduce the

adoption of product innovation. These signs are the opposite to the complementarity relationships described before, *i.e.*, $\delta_{dy} > 0$ and $\delta_{dc} < 0$. However, notice that in both cases we cannot exclude the possibility that the overall effect is not significant as the probability of adoption of each type of strategy varies from negative to positive along the 90% confidence interval. Furthermore, we also report how the probability of each innovation profile changes with the shift in the competition regime. Observe thus, that after liberalization, not adopting at all is less likely but on the other hand the probability of adopting both innovations remains mostly unchanged. The change in innovation patterns after the liberalization affects firms that specialize in either product or process innovation only.

5 Concluding Remarks

Arrow (1962) distinguished between development and adoption of innovations and argued that the Schumpeterian view does not hold when we refer to the latter. The distinction might not be relevant for research intensive industries such as aircraft engineering, biotechnology, or the pharmaceutical industry, but it is important for end user oriented goods. In these industries the innovative process reduces almost exclusively to the purchase and application of new production, distribution, and commercialization methods that either introduce new designs or help reduce the cost of selling the existing ones. If competition was to facilitate the adoption of innovations more than monopolistic environments, fostering competition will not only enhance welfare in a static manner by means of price reductions, but it will also induce dynamic effects through the adoption of innovations. In such cases, fostering competition could also facilitate the introduction of new varieties that increase the number and quality of products sold, or, alternatively, the adoption of technological improvements that reduce the costs of production. From an opposing perspective, it could be argued that failing to liberalize some specific industries might not be such a bad policy if competition were instead to diminish the prospects of long term cost reductions or the introduction of new products or services. Protectionist and "National Champion" industrial policies could therefore be justified in such circumstances.

The evidence documented in this paper partially vindicate opposing schools of thought (*i.e.*, we disappoint everybody up to certain extent). Our results supports Schumpeter's "pro-monopoly" position but only for the case of cost reducing innovations. Our results also back up Arrow's "pro-competitive" position when demand enhancing innovations are considered. More importantly, in addition to distinguishing the nature of the innovation, our estimates reveal that competitive pressure translates into changes in innovation only through changes in the scale of production, which

has frequently been assumed to be an exogenous determinant of innovations both in theoretical and empirical studies.

The advantage of our flexible econometric approach is that we can identify the channels through which competitive pressure translates into an incentive to innovate more or less. We treat firms as organizations that decide jointly on innovation and scale and we characterize the profit function as supermodular in product innovation and scale as well as being submodular in product and process innovations. In other words, it is the increase in production that triggers the increase in demand enhancing innovation and reduces the incentive to engage in cost reducing innovation.

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Appendix

A Likelihood Function

Profit function (1) includes includes four differentiated structural error components $(\epsilon_{d\,i}, \epsilon_{c\,i}, \epsilon_{y\,i}, \epsilon_{\pi\,i})$, whose realizations uniquely determine the observed optimal choice of $(x_{d\,i}, x_{c\,i}, x_{y\,i}, \pi_i)$. In order to estimate the model we assume that the vector of unobservable returns follows an unrestricted multivariate normal distribution.

The Joint Density of Scale and Profits. To write the likelihood function we first condition on the two continuous variables of the model, *i.e.*, the scale and profits. First, from equation (3), the unobserved return associated to the scale is

$$\epsilon_{y\,i} = \gamma x_{y\,i} - \theta_y - \delta_{dy} x_{d\,i} - \delta_{cy} x_{c\,i}, \tag{A.1}$$

and next we rewrite the profit equation (1) as follows

$$\epsilon_{p\,i} = \pi_i - \theta_\pi - \theta_d x_{d\,i} - \theta_c x_{c\,i} - \delta_{dc} x_{d\,i} x_{c\,i} + (\gamma/2) x_{y\,i}^2, \tag{A.2}$$

where we define $\epsilon_{p\,i}$ as the total unobserved return of any strategy other than the scale, that is

$$\epsilon_{p\,i} = \epsilon_{\pi\,i} + \epsilon_{d\,i} x_{d\,i} + \epsilon_{c\,i} x_{c\,i}. \tag{A.3}$$

Because of our normality assumptions on the distribution of $\boldsymbol{\epsilon}_i$, it follows that $\epsilon_{p\,i}$ is also normally distributed with zero mean and variance

$$\sigma_{p\,i}^2 = \sigma_\pi^2 + (\sigma_d^2 + 2\sigma_d\sigma_\pi\rho_{d\pi}) x_{d\,i} + (\sigma_c^2 + 2\sigma_c\sigma_\pi\rho_{c\pi}) x_{c\,i} + 2\sigma_d\sigma_c\rho_{dc} x_{d\,i} x_{c\,i}. \tag{A.4}$$

Thus, the join density of $\epsilon_{y\,i}$ and $\epsilon_{p\,i}$ is given by

$$g(\epsilon_{y\,i}, \epsilon_{p\,i}) = (\sigma_y \sigma_{p\,i})^{-1} \phi_2(\epsilon_{y\,i}/\sigma_y, \epsilon_{p\,i}/\sigma_{p\,i}; \rho_{yp\,i}), \tag{A.5}$$

where the correlation coe□cient between $\epsilon_{y\,i}$ and $\epsilon_{p\,i}$ is

$$\rho_{yp\,i} = (\sigma_\pi \rho_{y\pi} + \sigma_d \rho_{dy} x_{d\,i} + \sigma_c \rho_{cy} x_{c\,i}) / \sigma_{p\,i}. \tag{A.6}$$

Notice that given the distribution of $\boldsymbol{\epsilon}_i$, and making use of (A.3), equations (1) and (3) define a transformation from $(\epsilon_{y\,i}, \epsilon_{p\,i})$ to $(x_{y\,i}, \pi_i)$. The Jacobian of the inverse transformation given by equations (A.1) and (A.2) is

$$\boldsymbol{J} = \begin{vmatrix} \dfrac{\partial \epsilon_{y\,i}}{\partial x_{y\,i}} & \dfrac{\partial \epsilon_{y\,i}}{\partial \pi_i} \\ \dfrac{\partial \epsilon_{p\,i}}{\partial x_{y\,i}} & \dfrac{\partial \epsilon_{p\,i}}{\partial \pi_i} \end{vmatrix} = \begin{vmatrix} \gamma & 0 \\ -\gamma x_{y\,i} & 1 \end{vmatrix} = \gamma > 0. \tag{A.7}$$

The absolute value of the Jacobian of the inverse transformation is di□erent from zero because of the assumption that profits are concave in $x_{y\,i}$. Thus, equations (1) and (3) define a one-to-one transformation from $(\epsilon_{y\,i}, \epsilon_{p\,i})$ to $(x_{y\,i}, \pi_i)$ so that the joint density of $(x_{y\,i}, \pi_i)$ is

$$g(x_{y\,i}, \pi_i) = (\sigma_y \sigma_{p\,i})^{-1} \phi_2(\epsilon_{y\,i}/\sigma_y, \epsilon_{p\,i}/\sigma_{p\,i}; \rho_{yp\,i})\gamma, \tag{A.8}$$

which depends on the values of $x_{d\,i}$ and $x_{c\,i}$ through quations (A.1) and (A.2).

Probability of Innovation Profile Choice. The adoption of innovations is determined by conditions (9a)–(9c), which also depends on the unobserved returns on the scale and profits from other activities. Therefore, we first rewrite those equations conditioning on $\epsilon_{y\,i}$ and $\epsilon_{p\,i}$, and second, we derive the probabilities of observing each of the four possible innovation profiles. Thus we write

$$\epsilon_{d\,i} = h_{d\,i} + \epsilon_{d.yp\,i}, \tag{A.9a}$$

$$\epsilon_{c\,i} = h_{c\,i} + \epsilon_{c.yp\,i}, \tag{A.9b}$$

where $h_{d\,i}$ and $h_{c\,i}$, are the expectations of $\epsilon_{d\,i}$ and $\epsilon_{c\,i}$, conditional on $\epsilon_{y\,i}$ and $\epsilon_{p\,i}$ respectively; that is

$$h_{d\,i} = \sigma_d \frac{(\rho_{dy} - \rho_{dp\,i}\rho_{yp\,i})\epsilon_{y\,i}/\sigma_y + (\rho_{dp\,i} - \rho_{dy}\rho_{yp\,i})\epsilon_{p\,i}/\sigma_{p\,i}}{1 - \rho_{yp\,i}^2}, \tag{A.10a}$$

$$h_{c\,i} = \sigma_c \frac{(\rho_{cy} - \rho_{cp\,i}\rho_{yp\,i})\epsilon_{y\,i}/\sigma_y + (\rho_{cp\,i} - \rho_{cy}\rho_{yp\,i})\epsilon_{p\,i}/\sigma_{p\,i}}{1 - \rho_{yp\,i}^2}, \tag{A.10b}$$

and where the correlations between $\epsilon_{p\,i}$ and $\epsilon_{d\,i}, \epsilon_{c\,i}$ are

$$\rho_{dp\,i} = (\sigma_\pi\rho_{d\pi} + \sigma_d x_{d\,i} + \sigma_c\rho_{dc}x_{c\,i})/\sigma_{p\,i}, \tag{A.11a}$$

$$\rho_{cp\,i} = (\sigma_\pi\rho_{c\pi} + \sigma_c x_{c\,i} + \sigma_d\rho_{dc}x_{c\,i})/\sigma_{p\,i}, \tag{A.11b}$$

so that $\epsilon_{d.yp\,i}$, $\epsilon_{c.yp\,i}$ are normal variables that, by construction, are independent of $\epsilon_{y\,i}$ and $\epsilon_{p\,i}$. They have variances

$$\sigma_{d.yp\,i}^2 = \sigma_d^2\left[1 - \frac{\rho_{dy}^2 + \rho_{dp\,i}^2 - 2\rho_{yp\,i}\rho_{dy}\rho_{dp\,i}}{1 - \rho_{yp\,i}^2}\right], \tag{A.12a}$$

$$\sigma_{c.yp\,i}^2 = \sigma_c^2\left[1 - \frac{\rho_{cy}^2 + \rho_{cp\,i}^2 - 2\rho_{yp\,i}\rho_{cy}\rho_{cp\,i}}{1 - \rho_{yp\,i}^2}\right], \tag{A.12b}$$

and covariance given by

$$\text{cov}(\epsilon_{d.yp\,i}, \epsilon_{c.yp\,i}) = \sigma_d\sigma_c\left[\rho_{dc} - \frac{\rho_{dy}\rho_{cy} + \rho_{dp\,i}\rho_{cp\,i} - \rho_{yp\,i}(\rho_{dy}\rho_{cp\,i} + \rho_{dp\,i}\rho_{cy})}{1 - \rho_{yp\,i}^2}\right]. \tag{A.13}$$

Next, we substitute the unobserved returns to innovations given by equations (A.9a) and (A.9b) into conditions (9a)–(9c) and after rearranging terms we get

$$q_{d\,i}\epsilon_{d.yp\,i} > -q_{d\,i}(k_{d\,i} + \delta x_{c\,i}), \tag{A.14a}$$

$$q_{c\,i}\epsilon_{c.yp\,i} > -q_{c\,i}(k_{c\,i} + \delta x_{d\,i}), \tag{A.14b}$$

$$q_{c\,i}\epsilon_{s.yp\,i} > -q_{c\,i}\big[k_{c\,i} + \delta/2 + s_i(k_{d\,i} + \delta/2)\big], \tag{A.14c}$$

where

$$k_{d\,i} = \kappa_{d\,i} + h_{d\,i}, \tag{A.15a}$$

$$k_{c\,i} = \kappa_{c\,i} + h_{c\,i}, \tag{A.15b}$$

and

$$\epsilon_{s.yp\,i} = \epsilon_{c.yp\,i} + s_i \epsilon_{d.yp\,i}, \tag{A.15c}$$

which is a normal variable with zero mean and variance equal to

$$\sigma^2_{s.yp\,i} = \sigma^2_{d.yp\,i} + \sigma^2_{c.yp\,i} + 2 s_i \sigma_{d.yp\,i} \sigma_{c.yp\,i} \rho_{dc.yp\,i}. \tag{A.16}$$

Furthermore, the correlation coe□cients among $\epsilon_{s.yp\,i}$ and $\epsilon_{d.yp\,i}, \epsilon_{c.yp\,i}$ are

$$\rho_{ds.yp\,i} = (\sigma_{c.yp\,i} \rho_{dc.yp\,i} + s_i \sigma_{d.yp\,i}) / \sigma_{s.yp\,i}, \tag{A.17a}$$

$$\rho_{cs.yp\,i} = (\sigma_{c.yp\,i} + s_i \sigma_{d.yp\,i} \rho_{dc.yp\,i}) / \sigma_{s.yp\,i}. \tag{A.17b}$$

Consider now the probability that firm i adopts both innovations, $i.e.$, $x_{d\,i} = 1$, and $x_{c\,i} = 1$. Then, conditional on $\epsilon_{y\,i}$ and $\epsilon_{p\,i}$, conditions (8a)–(8c) must hold; that is

$$\epsilon_{d.yp\,i} > -k_{d\,i} - \delta, \tag{A.18a}$$

$$\epsilon_{c.yp\,i} > -k_{c\,i} - \delta, \tag{A.18b}$$

$$\epsilon_{s.yp\,i} > -k_{d\,i} - k_{c\,i} - \delta. \tag{A.18c}$$

There are two cases of interest depending on the value of δ:

1. $\delta \leq 0$. In this case the last of the above inequalities does not bind. This case corresponds to the bottom of Figure 1 where $S_i(1,1)$ is rectangular and thus, the probability of adopting both innovations becomes

   $$\Pr(x_{d\,i} = 1, x_{c\,i} = 1) = \Pr(\epsilon_{d.yp\,i} > -k_{d\,i} - \delta, \epsilon_{c.yp\,i} > -k_{c\,i} - \delta), \tag{A.19}$$

   which, given our assumption of joint normal distribution, leads to

   $$\Pr(x_{d\,i} = 1, x_{c\,i} = 1) = \Phi_2\left(\frac{k_{d\,i} + \delta}{\sigma_{d.yp\,i}}, \frac{k_{c\,i} + \delta}{\sigma_{c.yp\,i}}; \rho_{dc.yp\,i}\right). \tag{A.20}$$

$\Phi_2(\cdot;\rho)$ is the cumulative density function of a standard bivariate normal distribution with correlation coe□cient ρ, which in this case is the correlation coe□cient between $\epsilon_{d.yp\,i}$ and $\epsilon_{c.yp\,i}$ (or equivalently the correlation between $\epsilon_{d\,i}$ and $\epsilon_{c\,i}$ conditional on $\epsilon_{y\,i}, \epsilon_{p\,i}$)

$$\rho_{dc.yp\,i} = \text{cov}(\epsilon_{d.yp\,i}, \epsilon_{c.yp\,i})/(\sigma_{d.yp\,i}\sigma_{c.yp\,i}). \tag{A.21}$$

2. $\delta > 0$. Now the three inequalities (A.18a)–(A.18c) bind. This case corresponds to the top of Figure 1 where $S_i(1,1)$ is no longer rectangular. In order to compute the probability of adopting both innovations let split the region defined by the three inequalities (A.18a)–(A.18c) into the following two disjoint areas defined by

$$\epsilon_{d.yp\,i} > -k_{d\,i}, \tag{A.22a}$$

$$\epsilon_{c.yp\,i} > -k_{c\,i} - \delta, \tag{A.22b}$$

and by

$$-k_{d\,i} > \epsilon_{d.yp\,i} > -k_{d\,i} - \delta, \tag{A.23a}$$

$$\epsilon_{s.yp\,i} > -k_{d\,i} - k_{c\,i} - \delta, \tag{A.23b}$$

where the second set of inequalities make use of a change of basis so that the integration region defined in the $(\epsilon_{d.yp\,i}, \epsilon_{s.yp\,i})$ plane is rectangular.

Integrating the probability density function of $(\epsilon_{d.yp\,i}, \epsilon_{c.yp\,i})$ over the area defined by (A.22a) and (A.22b) we get

$$\Pr(\epsilon_{d.yp\,i} > -k_{d\,i}, \epsilon_{c.yp\,i} > -k_{c\,i} - \delta) = \Phi_2\left(\frac{k_{d\,i}}{\sigma_{d.yp\,i}}, \frac{k_{c\,i} + \delta}{\sigma_{c.yp\,i}}; \rho_{dc.yp\,i}\right), \tag{A.24}$$

and integrating the probability density function of $(\epsilon_{d.yp\,i}, \epsilon_{s.yp\,i})$ over the region defined by (A.23a)–(A.23b) we have

$$\begin{aligned}&\Pr(-k_{d\,i} > \epsilon_{d.yp\,i} > -k_{d\,i} - \delta, \epsilon_{s.yp\,i} > -k_{d\,i} - k_{c\,i} - \delta)\\ &\quad= \Phi_2\left(\frac{k_{d\,i}+\delta}{\sigma_{d.yp\,i}}, \frac{k_{d\,i} + k_{c\,i} + \delta}{\sigma_{s.yp\,i}}; \rho_{ds.yp\,i}\right) - \Phi_2\left(\frac{k_{d\,i}}{\sigma_{d.yp\,i}}, \frac{k_{d\,i} + k_{c\,i} + \delta}{\sigma_{s.yp\,i}}; \rho_{ds.yp\,i}\right).\end{aligned} \tag{A.25}$$

Finally, combining (A.24), and (A.25) we obtain the probability that a firm engages in both product and process innovation as

$$\begin{aligned}\Pr(x_{d\,i} = 1, x_{c\,i} = 1) = {}&\Phi_2\left(\frac{k_{d\,i}}{\sigma_{d.yp\,i}}, \frac{k_{c\,i} + \delta}{\sigma_{c.yp\,i}}; \rho_{dc.yp\,i}\right) +\\ &\Phi_2\left(\frac{k_{d\,i}+\delta}{\sigma_{d.yp\,i}}, \frac{k_{d\,i} + k_{c\,i} + \delta}{\sigma_{s.yp\,i}}; \rho_{ds.yp\,i}\right) - \Phi_2\left(\frac{k_{d\,i}}{\sigma_{d.yp\,i}}, \frac{k_{d\,i} + k_{c\,i} + \delta}{\sigma_{s.yp\,i}}; \rho_{ds.yp\,i}\right).\end{aligned} \tag{A.26}$$

We can determine the probabilities of adopting each innovative profile in a similar manner. To provide a general notation, let's define the indicator variable I_i as

$$I_i = \begin{cases} 1 & \text{if} \quad s_i\delta > 0, \\ 0 & \text{if} \quad s_i\delta \leq 0. \end{cases} \tag{A.27}$$

Then, since $x_{d\,i}$ and $x_{c\,i}$ may take only values in $\{0, 1\}$, we have

$$\begin{aligned} \Pr(x_{d\,i}, x_{c\,i}) = \Phi_2 &\left(q_{d\,i} \frac{k_{d\,i} + \delta[I_i - x_{c\,i}(2I_i - 1)]}{\sigma_{d.yp\,i}}, q_{c\,i} \frac{k_{c\,i} + \delta x_{d\,i}}{\sigma_{c.yp\,i}}; s_i \rho_{dc.yp\,i} \right) \\ &+ I_i s_i \left[\Phi_2 \left(\frac{k_{d\,i} + \delta}{\sigma_{d.yp\,i}}, q_{c\,i} \frac{k_{c\,i} + \delta/2 + s_i[\kappa_{d\,i} + \delta/2]}{\sigma_{s.yp\,i}}; q_{c\,i} \rho_{ds.yp\,i} \right) \right. \\ &\left. - \Phi_2 \left(\frac{k_{d\,i}}{\sigma_{d.yp\,i}}, q_{c\,i} \frac{k_{c\,i} + \delta/2 + s_i[2k_{d\,i} + \delta/2]}{\sigma_{s.yp\,i}}; q_{c\,i} \rho_{ds.yp\,i} \right) \right]. \end{aligned} \tag{A.28}$$

The Likelihood Function. Finally, we write the unconditional probability of observing a firm with specific strategy choices by multiplying the conditional probability of a given innovation profile (A.28), by the join density of the distribution of scale and profits from other activities (A.8), to obtain the contribution of observation i to the logarithm of the likelihood function

$$\begin{aligned} \ln \mathcal{L}_i(\Theta | x_{y\,i}, \pi_i, x_{d\,i}, x_{c\,i}) = \ln \gamma - \ln \sigma_y - \ln \sigma_{p\,i} + \ln \phi_2(\epsilon_{y\,i}/\sigma_y, \epsilon_{p\,i}/\sigma_{p\,i}; \rho_{yp\,i}) \\ + \ln \left[\Phi_2 \left(q_{d\,i} \frac{k_{d\,i} + \delta[I_i - x_{c\,i}(2I_i - 1)]}{\sigma_{d.yp\,i}}, q_{c\,i} \frac{k_{c\,i} + \delta x_{d\,i}}{\sigma_{c.yp\,i}}; s_i \rho_{dc.yp\,i} \right) \right. \\ + I_i s_i \Phi_2 \left(\frac{k_{d\,i} + \delta}{\sigma_{d.yp\,i}}, q_{c\,i} \frac{k_{c\,i} + \delta/2 + s_i[\kappa_{d\,i} + \delta/2]}{\sigma_{s.yp\,i}}; q_{c\,i} \rho_{ds.yp\,i} \right) \\ \left. - I_i s_i \, \Phi_2 \left(\frac{k_{d\,i}}{\sigma_{d.yp\,i}}, q_{c\,i} \frac{k_{c\,i} + \delta/2 + s_i[2k_{d\,i} + \delta/2]}{\sigma_{s.yp\,i}}; q_{c\,i} \rho_{ds.yp\,i} \right) \right], \end{aligned} \tag{A.29}$$

where $\Theta = (\theta_d, \theta_c, \theta_y, \theta_\pi, \delta_{dc}, \delta_{dy}, \delta_{cy}, \gamma, \sigma_d, \sigma_c, \sigma_y, \sigma_\pi, \rho_{dc}, \rho_{dy}, \rho_{d\pi}, \rho_{cy}, \rho_{c\pi}, \rho_{y\pi})'$ is the vector of parameters of the model.