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Competitive Pressure and the Adoption of Complementary Innovations

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Abstract

Liberalization of the European automobile distribution system in 2002 limits the ability of manufacturers to impose vertical restraints, leading to a substantial restructuring of the industry and increasing the competitive pressure among dealers. We estimate an equilibrium model of profit maximization to evaluate how dealers change their innovation strategies with this regime change. Using French data we evaluate the existence of complementarities among adoptions of innovations and the scale of production. We conclude that as firms expand their scale of production they concentrate their effort in one type of innovation only. Results are robust to the existence of unobserved heterogeneity.

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

JEL Codes: C35, L86, O31.

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1 Introduction

The question of how the intensity of competition in a market affects firm incentives to improve their products and processes is a long-standing one in economics.[1] As continued innovation ultimately determines the growth possibilities of an economy, policies aimed at increasing the (static) competitiveness of a market also have to be evaluated considering their impact on long-term innovativeness of a sector or an economy. Given that incentives to innovate depend on the rents expected by an innovative firm, there has been a lively debate on which market structure (and the associated rents) is most conducive to innovative behavior. Much of this debate has focused on a single dimension of innovative activity, while innovative activity is typically a complex process involving multiple decisions and stages. Our paper adds to this debate by addressing some of these aspects. It aims to capture the third part of the Schumpeterian trilogy —diffusion or adoption of innovations—and recognizes that potential adopters of innovations can choose among different innovations.

Specifically, we limit our study to a particular industry setting, the French car dealer industry, and consider the adoption of two software technologies aimed at improving different aspects of firm performance triggered by a change in regulation in the industry. This is interesting for several reasons: First, existing studies pay little attention to the *users* of an innovation. Thus, while we would not typically think of car dealers as innovators in the software industry, the ultimate contribution of information and communication technologies (ICT) on economic growth will depend on the extent to which they diffuse throughout the economy. Second, the adoption of different software technologies may be *interdependent*. That is, adoption of one technology may make the adoption of others more attractive (if they are complements), or adoption of one may foreclose

[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 War II contributions.

adoption of another (if they are substitutes in their functionality or if the firm's budget constraint does not permit adoption of both). Third, rather than relying on variation across different industries with numerous unobserved structural differences, we capture a change in competitive intensity through a regulatory regime change in a *single industry*.

What is the effect of an increase in competitive pressure on innovation, and *how is competitive pressure transmitted if firms choose multiple strategies simultaneously?* Our approach to answering this question builds on four basic pillars: (*i*) we distinguish between demand enhancing and cost reducing innovations; (*ii*) we allow firms to make adoption decisions simultaneously with other strategies, most importantly the scale of production; (*iii*) we let these strategies generate return complementarities when used jointly; and (*iv*) our estimations control for the possibility that unobservable factors drive the observed correlations among firms' decision variables.

The many existing theoretical models arrive at conflicting results of the effect of market structure on the innovativeness of firms. The Schumpeterian view argues that firms with market power have the strongest incentive to innovate as their monopolistic position allows them to capture innovation rents. However, in competitive markets markups are smaller, increasing aggregate demand, enabling more cost efficient firms to sell more at lower prices. Moreover, in the case of product innovations, competitive pressure may trigger additional product differentiation, which increases the sustainable markup that firms can charge their customers. The list of refinements and further issues explored in this general setting is extensive. 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) identifies the countervailing effect of own demand shifts following 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 in competitive or monopolistic settings differ depending on whether entry is free or restricted. With this canvas of possibilities, it is not surprising that Gilbert (2006, §I) notes 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."*[2] Thus, contrary to the practice of pooling data across industries and countries, empirical analysis should take into account the above arguments by focusing on institutions and features of specific industries. We attempt to do precisely that in this paper.

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) 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.

[2] 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.

Innovations are only one of the many strategies that firms choose together with production, pricing, advertising, *et cetera*. Following Milgrom and Roberts (1990), we treat 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. The scale of production seems particularly important, and the one whose effects on innovation have been studied most thoroughly. We therefore assume that firms decide simultaneously how much to produce and whether they should adopt one or more innovations or not. The scale of production is typically an explanatory variable of innovation activities 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 (under reasonable assumptions) 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] Holmes, Levine, and Schmitz (2008) argue that precisely this simultaneity leads to monopolistic firms having a lower incentive to adopt innovations than competitive ones. The reason is that adopting a process innovation requires a temporary reduction in scale —"switchover disruptions" in their terminology— and since monopolies forego larger rents with every unit temporarily lost than competitive firms, they tend to postpone such innovation decisions.

There may also be (positive or negative) complementarities arising across scale and adoption strategies. Complementarities offer several ways in which a more competitive environment may result in more innovation adoption: 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 (or less) innovation. We identify complementarities by assuming that firms maximize profits

[4] Cohen and Klepper (1996) consider the theoretical relationship between firm size and type of innovation using functional form assumptions driving many of the testable implications. Most importantly, scale is treated as an exogenous variable in their econometric specification.

by choosing all relevant strategies (i.e. scale and innovation adoption) simultaneously. The profit function may be supermodular and we use a flexible functional form to accommodate discrete strategies such as product and process innovation. Using a flexible functional form aims to avoid misspecification arising from restrictive functional forms that cannot accommodate certain innovation patterns, as suggested by Vives (2008). Our approach also allows for the existence of unobserved heterogeneity in the form of unobserved returns to the firms' strategies, which may be be correlated with each other. We 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.

We are interested in evaluating the impact of competitive pressure on the adoption of different kinds of innovations and identifying how the effect is transmitted. Syverson (2004) suggests using population density as a measure of how competitive markets are. More densely populated areas require more firms to serve it, thus enabling consumers to switch suppliers and therefore leading to larger degree of product substitution. According to Vives (2008, §1), this is a useful measure of competitive pressure both with and without entry. Population density identifies competitive pressure through variations across markets and time. In our study, 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 adopt an innovation.[5]

[5] The direct effect of antitrust regulation on innovation is a largely 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.

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. 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.

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 adoption decisions we consider and presents preliminary evidence on the existence of complementarities. Section 3 introduces the econometric model and shows 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, each successively relaxing restrictions on the existence of complementarities and unobserved heterogeneity. We then conduct various specification tests and discuss the estimation bias of an increase in competitive pressure if complementarities were ignored. We also evaluate the direct and indirect effects of an increase in competitive pressure on all strategies simultaneously by simulating firms' profiles and evaluating them at the parameter estimates and firm and market characteristics in our sample. Section 5 concludes.

2 Data and Institutional Background

We study the French car dealership industry between 2000 and 2004. The change in regulation in 2002 constitutes an interesting natural experiment that provides us with an unusual, but useful measure of increased competitive pressure. Specifically, this time period includes a substantial regime change in the vertical restrains allowed by the European Commission in the automobile distribution system. While a 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, which the regulatory change basically did, increases competition among dealers. This lets us study how an increase in competitive pressure affects scale and different innovation choices, both directly on their associated returns, and indirectly through the potential complementarities among these strategies. Our data contain dealer specific information on the use of different software as well as the associated profits of these firms. This allows us to identify the parameters of an equilibrium model of innovation behavior in the presence of complementarities among firms' strategies.

We first provide a quick overview of the liberalization of the automobile distribution system in Europe and argue 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 suggesting possible complementarities and a significant change in 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 demanded 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 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.

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 aimed primarily 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]

Until 2002 there were *main dealers* and *sub-dealers*. Main dealers had contracts with car manufacturers while sub-dealers held contracts with a main dealer, who supplied them with parts, vehicles, and technical support. After 2002, sub-dealers either gained the authorized repairer status,

[6] This subsection draws on Brenkers and Verboven (2006, §1-2,8) and Brenkers and Verboven (2008, §2.3), as well as on the data collected by London Economics in its June 2006 report to the EC DG Competition on "Developments in Car Retailing and After-Sales Markets Under Regulation No. 1400/2002."

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

or most frequently, they left the distribution network. This is important because the reorganization of the distribution network of the larger brands affects the output of the remaining dealers. In France the total number of dealerships fell 21% from 2002 to 2003 thus leading to an increase in sales per dealer.[8]

How does the removal of any of these restrictions enhance competition? The restructuring of the distribution system that follows it increases the concentration among existing dealer groups linked to the dominant manufacturers. In this sense it could be expected that the change in regulation led to an increase in market power rather than to an increase in competitive pressure. However, this ignores several issues. Larger dealers are more likely to comply with more stringent quality standards set by manufacturers and thus, concentration may lead to an increase in quality of service, perhaps, through the adoption of innovations. Larger dealers are also more likely to engage in multi-brand operations, therefore intensifying not only intra-brand competition but also inter-brand competition.[9] Lastly, exit of many dealers left many locations vacant in a densely populated market, which eased the entry of distributors of Asian manufacturers, thus limiting the market power of a more concentrated distribution industry. It is important to note that the increase in sales per dealer was not only due to the reduction of the total number of dealerships but also to an increase in competition. Automobiles experienced a substantial 12% price reduction in real terms between 1996 and 2004. This sales increase was also fostered by an increase in disposable income and by easy access to affordable financing options that allowed automobile sales outpace personal income growth.

[8] It is interesting to note that France and Italy were among the latest markets to embrace the restructuring of their distribution networks. This make France a better choice than many other countries where this process was already on its way by the time of adopting the new European regulation. If there are synergies between the scale of production and the adoption of innovations it will be better identified in the French case than in other European countries.

[9] By 2004, 20% of French dealers sold automobiles of different brands compared to only 12% two years earlier.

More generally, relaxing vertical restrains 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.[10] Additionally, dealers carrying the same brand of automobiles may now compete more fiercely for customers in other areas or through independent resellers. Rey and Stiglitz (1995) argue that this intensified intra-brand competition helps eliminate the existing double marginalization and lowers final prices paid by consumers. 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 automobile 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.

[10] 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		Pre-Expiry		Post-Expiry	
	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.

2.2 Software Adoption in Automobile Retailing

Our data include innovation strategies, sales, and accounting profits of the *Motor Vehicle Dealers* industry (SIC code 5511) in France 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 across the entire sample and pre- and post-expiry of the EU exemption: product innovation ($x_{d\,i}$); process innovation ($x_{c\,i}$); scale ($x_{y\,i}$); and accounting profits, (π_i). Notice the substantial increase in sales due to the reduction of dealerships that followed the liberalization of the European automobile distribution system.

The dataset we use is built from a large firm-level database on the usage of Information and Communication Technologies (*ICT*). Specifically, the data contain annual information on the software used in 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 adoption 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 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 *dèpartement* level data on gross domestic product (*GDP*) and the ln(*Population*) to proxy for market size. We also collected the surface area of these *dèpartements* to obtain a measure of population density for these markets. Furthermore, we

identified *dèpartements* 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 adoption of 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. For example, in the car dealer industry sales personnel is paid partly by commission, which has to be entered on the payroll every time a car sale is made. Therefore, operating costs of HR management software adopters are, *ceteris paribus*, likely to be lower than those of non-adopters. Thus HR accounts for process innovation $x_{c\,i}$ in our model.

APPS development software grew out of programming languages such as C++, Basic, or Fortran with 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.[11] APPS development software enables firms to develop IT infrastructure that can easily be scaled up to serve multiple locations. For example, firm-specific advanced replenishment systems for spare parts facilitates stocking different outlets and serving diverse consumer groups, enabling firms to grow and increase revenues more easily. Such systems are typically produced in-house with the help of APPS development software to incorporate the specifics of their

[11] 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.

Table 2: Distribution of Innovation Profiles

	All periods			Pre-Expiry			Post-Expiry		
	%	$\bar{x}_y$	$\bar{\pi}$	%	$\bar{x}_y$	$\bar{\pi}_i$	%	$\bar{x}_y$	$\bar{\pi}$
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.

business.[12] Internet applications prove critical not only in providing information about models, but also scheduling test-drives, checking availability, and finding out about financing conditions. According to a recent study, 30% of French customers are more likely to purchase a vehicle from a particular manufacturer when they are satisfied with the features of their website.[13] This implies that adopting APPS development software may allow car dealers to grow their revenues more easily, so that APPS accounts for product innovation $x_{d\,i}$ in our model.

Firms decide on the scale of production $x_{y\,i}$, measured as the logarithm of turnover in thousands of euros, together with the adoption of a demand-enhancing innovation $x_{d\,i}$, and the adoption of a cost-reducing innovation $x_{c\,i}$.[14] 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

[12] See 2007 report by Microfocus: "Tesco Creates a Common Operating Model for Quick Deployment," available at http://www.microfocus.com/000/Tesco_highres_US_V2_tcm21-15509.pdf.

[13] See the 2005 report by Capgemini: "Cars Online 04/05: Driving Growth Through Collaboration," and which is available at http://www.capgemini.com/resources/thought_leadership/cars_online_0405/.

[14] 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.

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.

2.3 Sampling Issues

Two issues need to be addressed when interpreting our results on the French car industry. First, which segment of the French car industry is featured in our sample and what does this imply for our results? Second, are the changes in software adoption specific to the industry that has experienced a change in regulation or are the adoption patterns driven by an economy-wide phenomenon? We discuss both questions in turn.

To address the first question, we briefly outline the sampling process of Harte-Hanks, the data provider. Harte-Hanks surveys firms based on a repeated process of comparing the firms already in the sample with the overall population of firms available from public sources. Firms with over 100 employees as well as subsidiaries of large firms (such as company-owned car dealerships) are then targeted for inclusion in the sample. For larger firms, Harte-Hanks therefore target a census of active firms with more than 100 employees, with smaller firms remaining in the sample if they have shrunk but once had more than 100 employees or if they are a subsidiary of a larger firm. If a targeted firm answers a sufficient number of questions on their IT use (usually above 60-80 per cent), it is included in the database. There is no indication that the firms refusing to answer outright or not answering enough questions are significantly different from the ones that do, suggesting that inclusion in the sample given the firm was in the sampling frame is random. The sampling process described above is consistent across different years, so that our sample consists of a similar selection of larger-than-average firms each year.[15]

Our sample includes larger dealers or those dealers that belong to a large dealer group. While the number of employees in a single dealership rarely exceeds 100, the average number of employees among the top 50 dealer groups in 2003 was 750.[16] These larger firms are among those who survive the restructuring of the industry in 2003 and thus the include those business units for which the adoption of innovations falls among the relevant decision variables. Smaller dealers only contemplated leaving the industry and thus, they will most likely were not innovating before 2002.[17] Thus, we do not model the process of exit and competitive destruction triggered by deregulation, but rather focus on the surviving firms only.

The second question could only be answered by comparing the dynamics of software adoption in technologically similar industries in France that did not experience a regulatory change. Unfortunately, we only have a limited number of firms in other retail industries and there is large variation in software usage, making statistical comparison difficult. Our limited data however suggest that the year-by-year change in APPS adoption showed opposite signs in other retail industries compared to SIC code 5511 (increasing in other retail, decreasing in 5511), and that

[15] Harte-Hanks' clients are typically large high-technology firms like IBM and Cisco. They use the information gathered to base their commercial decisions on, thus ensuring a high quality and accuracy of the data as their representatives would quickly find out during a sales call if Harte-Hanks' information was inaccurate. While clients do suggest including or dropping questions on particular technologies to maintain relevancy of their data (leading to, for example, exclusion of technologies that have diffused completely such as word processing software, or technologies that are not marketed actively anymore such as Computer-Aided Design tools), the clients do not influence the sampling process. A firm's propensity to purchase software from any of Harte-Hanks' clients, which could conceivably be another source of selection bias, does not play a role here.

[16] See page 56 of the London Economics report mentioned above.

[17] See the 2005 KPMG and FH-Gelsenkirchen report "Entwicklungen und Erfolgsfaktoren im Automobilvertrieb" (Recent Developments and Success Factors in Automobile Retailing) conducted by F. Dudenhffer, P. Wiegand, K. Neuberger, and J. Steinel, which is available at: (http://www.fh-gelsenkirchen.de/fb11/homepages/dudenhoeffer/studien/2005/EntwicklungenundErfolgsfaktorenimAutomobilvertrieb2005.pdf).

post-expiry of 1475/95, HR adoption increased in SIC code 5511 while it decreased in other retail industries. Thus, it would appear unlikely that changes in prices or profitability arising from sources other than the expiry of the EU regulation led to such diverging outcomes in technologically similar industries.

A third concern might be that our dummy variables for the respective applications do not pick up the true usage of HR and APPS software, in other words that there is significant measurement error in our adoption variables. We consider this unlikely given the importance of accuracy for the commercial value of the data (Harte-Hanks refunds data purchases for any samples with error levels above 5 per cent) and given that the data includes both externally purchased software of a given class (*e.g.*, Borland's Delphi as an APPS development program) as well as software developed in-house (*e.g.*, a customized HR system).

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.[18] 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.[19] Innovation indicators are dummy variables, which adds to the complexity of the

[18] 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.

[19] Accounting profits are not normally employed in empirical studies. We include turnover in the same spirit as the *productivity approach* evaluates the effectiveness of innovations by metrics such as output, exports, or labor

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.

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) 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

productivity. Including profits extends Miravete and Pernías (2006) by relaxing all their restrictive identification assumptions.

in each possible pair of strategies while ignoring all other differences among firms.[20] 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

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

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

[20] 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). Miravete and Pernías (2009) show that such a simple correlation analysis cannot capture the effect of complementarity when decision variables are, as in the present case, dichotomous. Indeed, these correlation measures will only capture correlation due to unobservable heterogeneity.

of innovations. We envision firm i choosing its scale and innovation profile to maximize the profit function $\pi_i(x_{d\,i}, x_{c\,i}, x_{y\,i})$.[21] 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.[22]

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[23] 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.[24]

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[21] It could be questioned whether our model is appropriate, *i.e.*, whether a dealer or a dealer group actually chooses these strategies or if manufacturers make these choices for them. Manufacturers do not have any legal competence on deciding over sales or any other decisions of dealers. Furthermore in 2004, there were only 388 manufacturer owned dealers out of 12,774 total dealers.

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

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

[24] 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

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 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

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

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

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

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.

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 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:

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

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

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

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

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:

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

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

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

These conditions imply that observing firm i adopting both innovations correspond to the following restrictions on the unobserved returns of product and process innovation $(\epsilon_{d\,i}, \epsilon_{c\,i})$:[25]

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

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

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

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:[26]

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

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

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

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

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

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

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

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

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

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

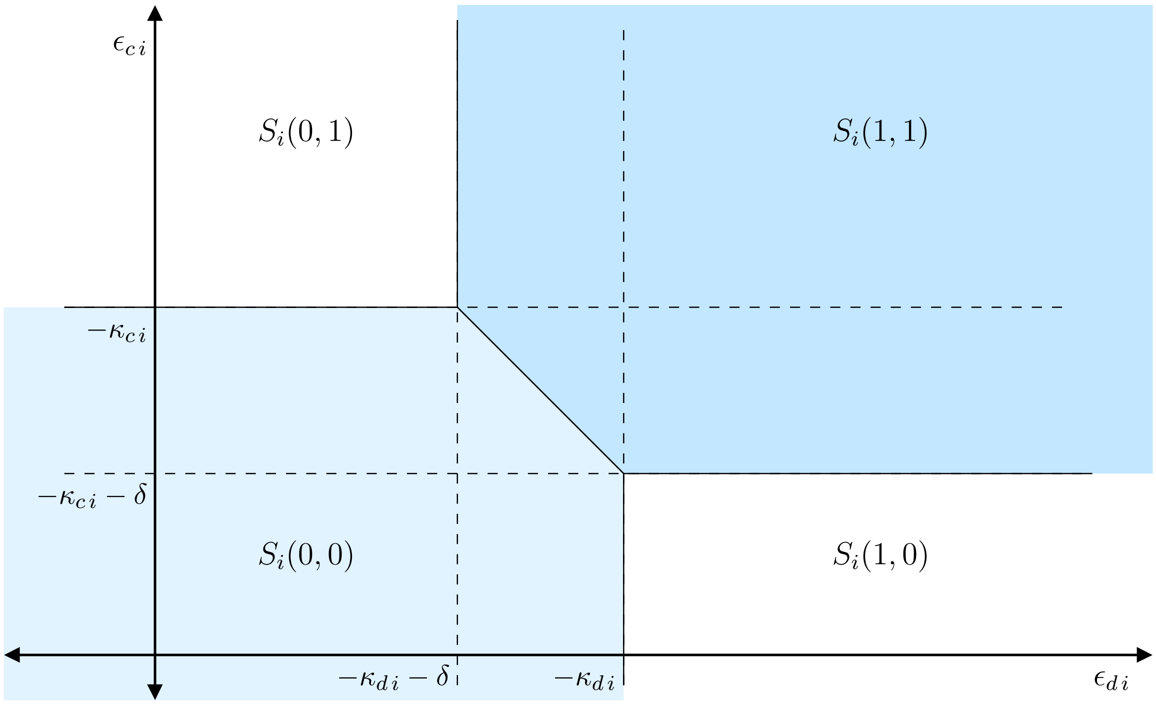
Figure 1 shows the shape of the $S_i(x_{d\,i}, x_{c\,i})$ regions for positive and negative values of δ. Notice that these disjoint regions are defined by the observed and unobserved return of profits associated to scale and innovations. Neither $\epsilon_{\pi\,i}$ nor θ_π appear in conditions (9a)–(9c). 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.[27]

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

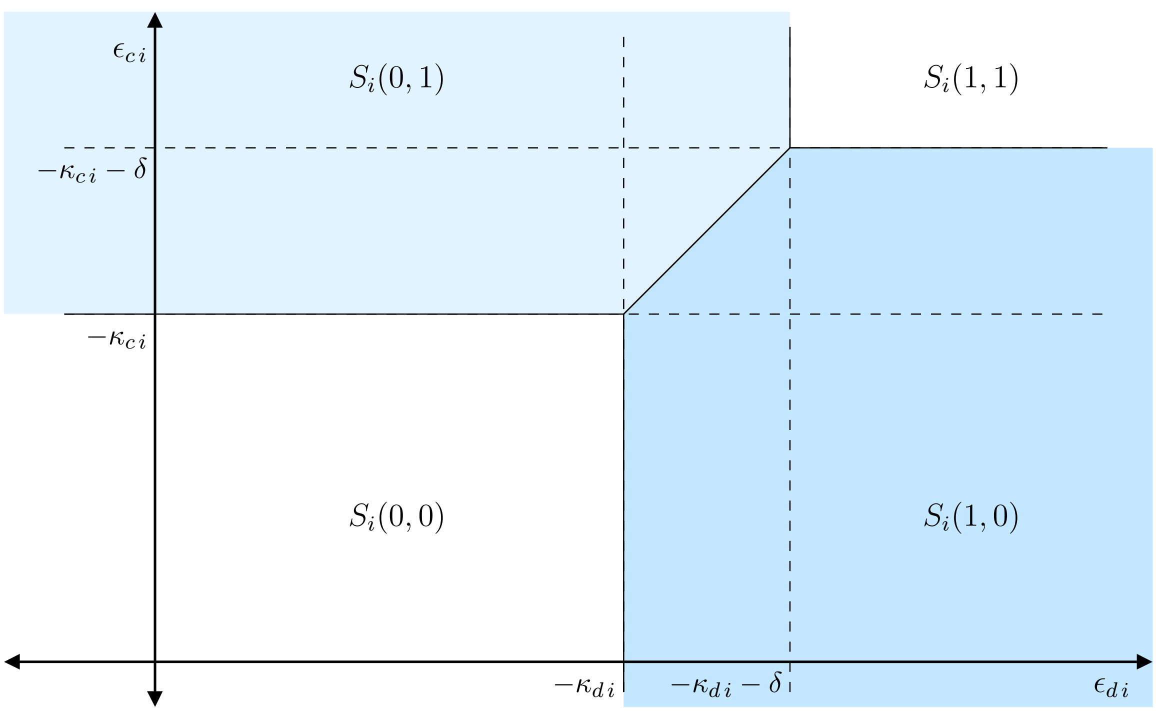
[27] As Figure 1 shows, the areas of integration corresponding to each innovation profile are not rectangular unless $\delta = 0$. This situation is common in the entry literature. Both Berry (1992) and Mazzeo (2002) encounter non-rectangular integrations areas similar to those of Figure 1. They resort 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.

Figure 1: Innovation Profile Defining Regions

(a) $\delta > 0$



(b) $\delta < 0$



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 $(\theta_d, \theta_c, \theta_y, \theta_\pi)$.

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 Empirical Results and Interpretation

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 to impose any *a priori* assumptions about the effect of any given regressor, say population density, on the returns to adoption or to expand production. These returns are precisely what we want to evaluate by estimating the model.

Table 4 presents the sample distribution of all regressors by competitive regime 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 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. *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.

2. 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 in purchasing power of potential customers across markets that may reflect price elasticity of demand in each local market.

3. ln(*Density*) is the logarithm of the population density of each market measured as the number of inhabitants per square kilometer. Density may have several possible effects. First, it is related to the cost of storage and car display. If this effect dominates, this variable should

Table 4: Sample Distributions of Exogenous Variables

	All periods		Pre-Expiry		Post-Expiry	
	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.

affect scale negatively. Second, we can 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 adoption in our case) and allow 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 Adoption and Scale

Table 5 evaluates the effect of liberalization in the European automobile distribution system while ignoring the effect of other potential covariates. Table 6 presents the estimates of four different vectors of $(\theta_d, \theta_c, \theta_y, \theta_\pi)$ of the general model described in Section 3. We find that although the inclusion of market characteristics improves the estimation, estimates of the liberalization effect (LIB) retain the same sign and significance, and estimates of complementarity effects, $(\delta_{dc}, \delta_{dy}, \delta_{cy})$ are robust to the inclusion of additional regressors. The same holds for the correlation among the unobservable returns of each strategy, in particular for the results of Model IV.

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.

Model I assumes away both potential complementarities among strategies and the existence of unobserved heterogeneity by assuming that unobserved returns are uncorrelated. Model II allows for the possibility of complementarities among strategies but not unobserved heterogeneity, while Model III allows for unobserved heterogeneity, but not complementarities. Model IV as the most general specification allows for correlation among strategies to be explained both by unobservable returns and complementarities. The likelihood ratio test in Table 7 always rejects the more restrictive model in favor of the more general one, leaving Model IV as our preferred specification. That is, both unobservable heterogeneity and complementarities matter in explaining simultaneous scale and product and process innovation decisions. Consequently, we will concentrate on the parameter estimates of Model IV.

We start by analyzing the effect of competitive pressure. The liberalization of the European distribution system does not have any significant direct effect on the returns to either product or process innovation. However, our model allows the effects of increased competitive pressure on innovation to be indirect through the change in the scale of production. The positive sign of the estimate of *LIB* on scale captures the effect of increased concentration among the surviving dealers as well as the documented competition effect due to lower prices. In turn, larger scale 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.

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 to compensate for the reduction in their markups. Firms choosing a larger scale are then more likely to adopt software technologies that facilitate their growth, i.e. demand-enhancing innovations. This may explain the need to restructure the distribution networks (something that happens not only in France but across Europe) by severing ties with sub-dealers and forcing them to leave the network. Similarly, the classical Schumpeterian view that a less competitive market favors innovation finds support, but only when considering cost reducing innovations. Again, this effect is indirect through the complementary relationships between strategies. Our results suggest that the ability to capture rents from a cost-saving innovation induces monopolistic firms to adopt them since they adopt them less frequently as 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 as shown in Table 6 . The return to adopting product innovations is larger in smaller markets while process innovation is favored in less affluent markets. The negative effect of ln(*Population*) is surprising although the overall effect on innovation adoption is uncertain since ln(*Population*) also favors larger-scale dealerships which, in turn, favor the adoption of product innovations. As for cost reducing innovations, one interpretation is 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 insignificant coefficient of population density as a static measure of competition intensity on innovation of any kind does not support the argument put forward by Syverson (2004). Note also that firms choose larger scales in wealthier markets but contrary to Syverson (2004) more dense markets feature smaller dealers. This suggests that the effect of costly storage dominates in an industry where space for display is scarce in dense cities.

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 potentially complementary firm strategies. 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. Following Model II, we would conclude that there are no complementarities among strategies and that the increase in competitive pressure does not significantly affect the scale of production or innovation activities. These results would be at odds with 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 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. Further, ignoring complementarities also affects the significance of many other estimates. In particular, liberalization 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 theory does not offer any guidance as to 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 comparison) is the correct one. All paired tests favor the comparatively more general over the restrictive specification. Model IV is the preferred specification, which allows for 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 using a Wald test where the null hypothesis is that these regressors are not jointly significant. 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. The exception however is *LIB*, the dummy variable that identifies the regime change. As this is our variable of interest however, we are especially interested in the transmission channels of increased competitive pressure even if there are no significant direct effects. We therefore kept *LIB* in all our equations. All the other excluded variables are neither jointly nor individually significant in the specification of any of the return equations.

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

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 may be more likely in these areas to find the expertise to adopt innovations that improve service or allow firms to provide services more efficiently.

2. *Near* designates the *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.

The 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 discussed in Section 2.1, the former regulation of this industry was known to expire in September of 2002. Thus, our definition of *LIB* may 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. In our estimations the estimates of *Y2001* and *Y2002* are not significant (either jointly or individually in each return equation), which strongly supports our claim that *LIB* was not anticipated and that it identifies an exogenous regime change.

4.3 Quantifying the Effect of Liberalization

The estimates of Table 7 only indicate the direct effect of each regressor on the corresponding returns to each strategy. Thus, we can conclude that increasing the change in scale triggered by a 1% increase of *GDP* per capita is equivalent to a 4% reduction in population density. 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. That is, firms in a liberalized market will choose an average scale equivalent to a firm in a 2% more populous market pre-liberalization.

These numbers are not necessarily useful 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 use our sample of firms to carry out a simulation exercise based on the estimates of Model IV from Table 6. Using the values 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, 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 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 an expected value of 0 and a covariance matrix given by our 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, adoption of product and process innovations, 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 (5,000 x 20) 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. In addition to 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. 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 is 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 complementarity effects 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 $'$000's of euros in the table). The median direct effect of liberalization is only 600€ while median profit synergies due to complementarities amount to 370€. However, the increase in profits after liberalizing the European automobile distribution system is not unambiguous as 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 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 led to an important overestimation of the effect of liberalization on scale. The increase in the scale is the key unambiguous effect of liberalization: the 90% confidence interval of simulations ranges between a 0.03% and a 44.91% increase in 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, in both cases the 90% confidence interval includes no change. Further, 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

In this paper, we study the French automobile market between 2000 and 2004 and their adoption of two software technologies. Developing an equilibrium model in which firms choose scale and the adoption of different enterprise software, we specifically ask if the regulatory regime change in 2002 which relaxed vertical restraints on car dealers and led to an increase in competitive pressure was associated with a change in the software adoption behavior and the optimal scale of operations (which is often treated as exogenous in other studies) of the firms in our sample.

Our estimation results suggest that competitive pressure translates into a change in adoption behavior via changes in the optimal scale of firms and that adoption strategies for both types of software are substitutes. Specifically, scale increases with increased competitive pressure, suggesting a consolidation of markets and concentration of fewer, larger firms and exit of smaller firms. This in turn leads to a change in adoption behavior as scale and the adoption of demand-enhancing software are complements, while firms tend to substitute demand-enhancing and cost-reducing innovations, *i.e.*, they are unlikely to adopt both.

Our findings partially vindicate both the pro-monopoly and the pro-competitive view (*i.e.*, we disappoint everyone to a certain extent). We find that an increase in competitive pressure led to an increased tendency to adopt demand-enhancing innovations, allowing firms to expand their scale of operations. Conversely, prior to the increase in competitive pressure, firms were more likely to adopt cost-reducing innovations, suggesting that being shielded from competition fosters the adoption of such innovations. This stems from the fact that the vertical restraints in place supported firms that were smaller (*i.e.*, operated on a smaller geographical scale) than in a more competitive market.

The flexible econometric approach we develop in this paper allows us to identify the different channels by which competition affects the adoption of new technologies. We find the profit function to be supermodular in demand-enhancing innovation and scale as well as submodular in cost-reducing and demand-enhancing 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. This result, if confirmed in other settings, is of interest to policymakers who will have to form ex-ante priors about the social welfare implications of specific types of innovations, as a policy shift can affect their adoption in different directions. More generally, the notion that the adoption of different innovations is likely to be a joint decision with scale and that adoption decisions may substitute for each other implies that future research should attempt to take into account these complementarities to adequately study the innovation adoption behavior of firms.

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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 $(x_{d\,i}, x_{c\,i}, x_{y\,i}, \pi_i)$. 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.*, scale and profits. First, from equation (3), the unobserved return associated to 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 joint 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 coefficient 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 different 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_{ci}, are the expectations of $\epsilon_{d\,i}$ and ϵ_{ci}, 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

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

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

and covariance given by

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

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

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

Furthermore, the correlation coefficients 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 coefficient ρ, which in this case is the correlation coefficient between $\epsilon_{d.yp\,i}$ and $\epsilon_{c.yp\,i}$ (or equivalently the correlation between $\epsilon_{d\,i}$ and $\epsilon_{c\,i}$ conditional on $\epsilon_{y\,i}, \epsilon_{p\,i}$)

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

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. To compute the probability of adopting both innovations, we 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

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

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.