8-2004

Technological diversification and economic performance: A within industry perspective

Patrick P. Steinemann
Merrill Lynch

Francisco Veloso
Carnegie Mellon University, fveloso@cmu.edu

Claudio Wolter
Carnegie Mellon University

Program in Strategy, Entrepreneurship and Technological Change
Working paper (second draft – August 2004)

TECHNOLOGICAL DIVERSIFICATION AND ECONOMIC PERFORMANCE: A WITHIN-INDUSTRY PERSPECTIVE

PATRICK P. STEINEMANN[1]
Merrill Lynch Financial Centre
Merrill Lynch International
2, King Edward Street, London, EC1A 1HQ, UK
e-mail: patrick_steinemann@ml.com
Phone: + 44 20 7995-4546
Fax: + 44 20 7995-0626

FRANCISCO VELOSO[2]
Program in Strategy, Entrepreneurship and Technological Change
Department of Engineering and Public Policy
Carnegie Mellon University
5000, Forbes Avenue, 15213-3890 Pittsburgh, PA, USA
e-mail: fveloso@cmu.edu
Phone: + 1 412 268-4640
Fax: + 1 412 268-3757
and
Faculdade de Ciências Económicas e Empresariais
Universidade Católica Portuguesa
Palma de Cima, 1639-023 Lisbon, Portugal
e-mail: fveloso@fcee.ucp.pt
Phone: + 351 21 721-4241
Fax: + 351 21 727-0252

CLAUDIO WOLTER
Program in Strategy, Entrepreneurship and Technological Change
Department of Engineering and Public Policy
Carnegie Mellon University
5000, Forbes Avenue, 15213-3890 Pittsburgh, PA, USA
e-mail: cwolter@cmu.edu
Phone: + 1 412 268-5609
Fax: + 1 412 268-3757

Please do not cite or distribute without permission of the authors. The usual caveat applies.

[1] Authors listed alphabetically
[2] Corresponding author

TECHNOLOGICAL DIVERSIFICATION AND ECONOMIC PERFORMANCE: A WITHIN-INDUSTRY PERSPECTIVE

Abstract

This study aims at a better understanding of how firms arrange and profit from their technological competencies. In particular, it presents a contribution to the diversification-performance literature by dealing with a still poorly researched aspect of diversification, namely technological diversification, while controlling for market diversification. Results suggest that firms that concentrate their technology assets in coherent groups outperform those that distribute their technology endowments across less related areas. The research also contributes to the literature on firm heterogeneity by focusing and exploring a single industry, automotive suppliers in the U.S. By working in one sector, it avoids the complications inherent in inter-industry cross-sectional analysis, while recognizing that firms make their strategy decisions within a single-industry, where most of their resources are concentrated.

Key words: Technological diversification, market diversification, financial performance, product and process firms, automotive supplier industry

JEL Classification: L20, L62, M10

INTRODUCTION

The boundaries of the firm[3] and its heterogenous productive resources have been of interest to economists ever since Coase (1937) published his seminal work. Nevertheless, the dominant industrial organization economics (IOE) framework that emerged thereafter used the industry as the unit of analysis and treated firms within the same industry as homogenous. Differences in firm performance were seen as a consequence of dissimilar structural factors (e.g. entry barriers) in the industries where these firms operated. In other words, this framework argued that firm behavior (in a profit maximizing sense) is constrained by the market structure, leading to industry-specific performance heterogeneity (Bettis 1981, Hawawini, Subramanian and Verdin 2003).

Even when new theoretical developments emerged in order to explain empirically observed differences among firms within the same industry, these differences were assigned to certain unique characteristics (e.g., some proprietary technology, geographical location), and to initial conditions in a path-dependent process, or perhaps some exogenous stochastic shock. In any event, firms were still viewed as homogenous since, given the same constraints, all of them would arrive at the same profit maximization solution.

As Nelson (1991) has argued, this is a rather limited view of what firms are about and it cannot explain most of firm heterogeneity observed in empirical studies. To account for such observations, an alternative perspective has emerged in the last decades in the Management literature. Although the importance of resources and its services to a firm had been originally discussed by Penrose (1959), the modern resource-based view (RBV) of the firm explicitly conceptualizes a company as a collection of productive resources and capabilities. Those that are valuable and difficult to imitate, substitute or trade enable the firm to maintain a competitive advantage relative its peers. Thus, the RBV research has focused on the creation, accumulation, and exploitation of these types of resources, also called *strategic assets* (Dierickx and Cool 1989, Peteraf 1993, Wernerfelt 1984).

One particular topic of relevance for the RBV of the firm relates to the role of resources in diversification decisions and the consequent impact of these decisions on firms' financial performance. Although many possible reasons for diversification have been identified, market failure in the case of firm-specific excess strategic assets is probably the most relevant one (Montgomery and Wernerfelt 1988, Peteraf 1993). Note that firm specificity arises not only from the intrinsic nature of the resource, but also from organizational learning with its use. This translates in a value of the resource for the firm exceeding its market value (Rubin 1973). And the existence of unused resources that cannot be traded in the open market is a major thrust for the search of alternative profitable opportunities to use them, leading to firm diversification.

This idea has generated a large number of empirical studies looking at how market diversification decisions affect firm performance (see Palich, Cardinal and Miller (2000) for a review). Most of them use broad samples of firms in multiple industries and address the issue of corporate diversification across these industries (Ramanujam and Varadarajan 1989). Overall, results tend to support a relatedness hypothesis (Rumelt 1982, Palepu 1985), according to which firms that enter closely related markets tend, on average, to have better performance.

Recently, there has been a growing interest in trying to understand the nature and role of the

[3]The boundaries of a firm can assume different configurations, depending on whether the firm is pursuing a strategy of vertical or horizontal integration, or diversification. The latter will be the object of interest in this paper.

firm's technological resource base in its competitive position, as well as the relationship between technological and market diversification (Breschi, Lissoni and Malerba 2003, Gambardella and Torrisi 1998, Silverman 1999). In fact, Penrose (1959) had already noted that many large firms in the U.S. economy tend to diversify into markets where they can exploit their superior technological capabilities and sustain a competitive advantage. Nevertheless, few empirical studies have dealt with this technological base in manufacturing, mainly due to difficulties in conceptualization and measurement.

This research contributes to the diversification-performance literature by dealing with and deepening our understanding of this still poorly researched aspect of diversification, namely technological diversification, while controlling for the variable traditionally explored in this literature, market diversification. In contrast to most previous works on diversification, this paper focuses on a single industry, the automotive supplier industry in the U.S. This approach enables a careful and detailed account of the firm's technological characteristics. It also recognizes the fact that, in general, firms (even large ones) are more likely to compete within a single industry, where most of their specialized resources, competencies and knowledge are concentrated (Chatterjee and Wernerfelt 1991, Penrose 1959). Finally, it avoids the complications and traps inherent in inter-industry analysis such as potentially different systematic risks, tax laws and accounting conventions across industries which might lead to biased results (Bettis 1981, Montgomery and Wernerfelt 1988).

The critical results suggest that manufacturing firms which organize their technological capabilities in a coherent fashion and around a core body of technical know-how will financially outperform their more technologically diverse counterparts. In other words, firms benefit and profit from economies of scope arising from the use of a common knowledge base underlying related technical areas of their manufacturing operations. We also find some limited support for the relatedness hypothesis, while noting important differences between produc- and process-based firms.

The present study also contributes to the literature on firm heterogeneity (Helfat 2000). It builds on the notion that patterns of technological diversification are different across sectors (Kodama 1986, Malerba 2002, Mowery and Nelson 1999, Pavitt, Robson and Townsend 1989), probing in detail how strategy and technology interact in an industry whose research intensity is not thought to be comparable to that of more thoroughly studied high-tech sectors (e.g. electronics and pharmaceuticals). Explicitly, the research aims at a better understanding of how firms arrange and profit from their technological competencies.

Finally, the results inform an emerging line of work looking into the critical difference between what firms know and what firms make (Brusoni, Prencipe and Pavitt 2001, Takeishi 2002). Since previous research (Gambardella and Torrisi 1998) suggests that diversification of technological knowledge – measured with patents – is positively associated with performance, our findings emphasize that what firms make may not be the same as what they know, complementing early assessments of this important difference. Knowledge embodied in patents and in manufacturing operations should not be viewed as substitutes, but rather as complements.

The paper is structured as follows: the next section presents the theoretical background including a brief overview of the RBV literature, with particular emphasis on diversification and its consequences to firm performance. This is followed by a framework for classifying manufacturing business segments and firms within the automotive supplier industry as product- or process-based ones. This framework is relevant since we understand that the two categories organize their technological competencies in distinct forms, and this impacts their diversification decisions and relative performance. Then, we present an overview of the literature on technological diversification and discuss its implications within the RBV. The following section describes our data, discusses the dependent, independent and control variables and lays out our econometric approach to test the relevant hypotheses. Empirical results are then presented, followed by an overall discussion of these results as well as possible limitations of this study. The last section concludes.

THEORY AND HYPOTHESES

The RBV of diversification

Before proceeding any further, it is useful to state what will be understood by market diversification, or simply diversification. In general terms, this is usually conceptualized as entry of a firm or business unit into new lines of activity, either by internal business development or acquisition (Ramanujam and Varadarajan 1989). More specific definitions were put forth by Gort (1962). While he saw diversification as an increase in the heterogeneity of markets served by a firm, he also noted that this heterogeneity could be identified by two complementary measures: the cross-elasticity of demand and the immobility of productive resources. Nevertheless, both measures are very difficult to observe in practice and a common strategy is to resort to Standard Industry Classification (SIC) codes to separate markets.

This is exactly what it is done in the present study, where a diversified firm is defined as one having a business segment in more than a single 4-digit SIC code defined industry. As is well known, the classification was developed for the U.S. Bureau of Census to measure economic activity in the U.S. To conform to diverse industry structures, it does not follow a single classification principle. However, for manufacturing activities it usually takes the standpoint of product classes, although in some cases raw materials and processes are also used as the main factors distinguishing industries. Nevertheless, the different criteria usually leads to the same classification (Gort 1962).

Diversification is among the most researched topics in the strategy literature and many reasons have been proposed for firms' diversification moves. The prevailing theory of diversification draws heavily on the RBV of the firm. According to the RBV, firms attempt to accumulate valuable, rare, inimitable and non-substitutable resources and use them in value-creating strategies to attain a sustainable competitive advantage and earn Ricardian rents (Eisenhardt and Martin 2000, Montgomery and Wernerfelt 1988). In any firm there will be an excess of services arising from the indivisibility of tangible and intangible acquired or developed strategic assets such as brand names, skilled personnel, efficient procedures and organization, research and development (R&D) capabilities, machinery, patents, technological knowledge, etc. To the extent that these resources are idiosyncratic or specific in nature and, therefore, there is a market failure for them due to high transaction costs (Peteraf 1993), there will be a strong incentive to exploit them via diversification. In other words, economies of scope[4] in the exploitation of excess resources will generate profitable opportunities for diversification into other markets. Alternatively, it is possible to see unused excess resources imposing a cost onto undiversified firms (Montgomery and Wernerfelt 1988).

[4]Economies of scope are understood here as defined by Panzar and Willig (1981), Rumelt (1982) and Teece (1980).

Naturally, resources are expected to lose in efficiency when deployed farther from their original use. Eventually, this will lead to a zero marginal return to diversification. Overall, this hypothesis leads to a positive relationship between diversification and firm performance, but with diminishing marginal returns, something originally alluded to by Coase (1937) under “decreasing returns to the entrepreneur function”. However, if in addition there are marginally increasing costs of diversification due to organizational inefficiencies, governance control losses, disincentives to employees and consequent shirking as the scope of the firm widens (Montgomery and Wernerfelt 1988, Palich et al. 2000, Rotemberg and Saloner 1994), market diversification will eventually have a negative impact on the firm’s financial performance. Therefore, an optimal level of diversification should exist, where the marginal return obtained from economies of scope equals the marginal cost arising from the “diseconomies” of organizational scale (Rumelt 1982).

Initial empirical tests in the IOE literature yielded no support for the RBV of diversification, finding no link between the variables of interest. Nonetheless, after Rumelt introduced his categorical classification of market diversification, based on both quantitative data and qualitative judgement, empirical results from the Management literature began to show such a systematic relationship between diversification and performance (Palepu 1985). Although Rumelt’s classification is not unconditionally superior to other methods of assessing firm diversification (Montgomery 1982), the key factor that he demonstrated was that not only the scale of diversification matters (as measured by simple product count in the IOE literature), but particularly the scope of diversification, that is, the degree of relatedness in the markets entered by a firm. Related diversifiers are supposed to be able to exploit economies of scope, creating and accumulating strategic assets more efficiently than competitors. In line with the RBV, by tapping into their core capabilities and generating *synergies* between business units or segments, they should have a better performance vis-à-vis low diversifiers or single business firms and unrelated diversifiers.

Although this paradigm has not been unanimously accepted, using a meta-analytic procedure to analyze 55 previous empirical studies on the diversification-performance link, Palich et al. (2000) found reasonable support for the hypothesis of firms benefitting from related diversification. On average, one can say that firms diversifying to related markets enjoy better performance. However, most empirical studies have found sub-samples of unrelated diversified firms with high performance as well (Bettis and Mahajan 1985, Chatterjee and Wernerfelt 1991, Varadarajan and Ramanujam 1987).

Market diversification and technology organization in manufacturing

In discussions of manufacturing industries and technological capabilities, a fundamental distinction is often made between products and processes, in the context of organizational structures, manufacturing operations (Hayes and Wheelwright 1979) and technological innovation. Early concepts of product and process distinction in organizational structures emerges from a discussion of organizational structure of General Motors and other industrial enterprises (Chandler 1962), where the term divisions is used for organizations along product lines, and departments for process-oriented or functional organizations in the so-called multidivisional form (M-form) of organization. Still today, the product division is the most common form of organization and is particularly pronounced in diversified firms and industrial conglomerates. Nonetheless, it has been shown that many companies which have combined related activities into a process-oriented organization by grouping core processes rather than products, are better able to coordinate similar tasks (Hammer and Stanton 1999). In many cases, such firms achieve superior performance through process standardization, lower overhead costs, and simplified interaction with suppliers and customers. Owens Corning, a company that supplies glass fibers, adhesives and coatings to the automobile industry, is one of the examples of a process organization cited by Hammer and Stanton (1999).

Hayes, Wheelwright and Clark (1988) distinguish between a product / market-focused organization and a technology / production-process-focused organization. The product / market-focused organization separates product groups into divisions that are highly decentralized. As a result, this organization is more responsive to market needs and more flexible when introducing new products. In contrast, the process-focused organization separates manufacturing plants according to process stages. Process organizations are able to better exploit economies of scale, but require more complex management structures with less flexibility. Supporting these distinct characteristics, Teece (1977) studied 26 international technology transfer projects in large multinational American companies and found substantial differences between “continuous flow process technology” firms, including chemicals and petroleum refining, and “product technology” firms (machinery).

In studies of the automobile industry, the role of product development for superior performance has been pointed out by several studies (Clark and Fujimoto 1991, MacDuffie, Sethuraman and Fisher 1996). Key performance parameters in automotive product development are: development lead time, product quality and productivity, which have been shown by Clark and Fujimoto (1991) to depend critically on superior capabilities in integrated engineering problem solving, and manufacturing efficiency (just in time and the lean manufacturing paradigm). The role of process development figures less prominently in the literature. Process development is not only important in industries with complex process technologies for a continued reduction of manufacturing costs, but also in support of efficient and high-quality launches of new products (Pisano 1997).

The distinction between product- and process-based firms rests upon the existence of capabilities and competencies in two dimensions. Product firms are defined through capabilities and skills relating to individual products or product lines, as an organizational consequence of their technological capabilities and focus of business activities on distinct product markets. As a consequence of the focus on differentiated products, product firms often secure the intellectual property of their highly engineered products through patents and trademarks, and continually invest in research and product development. Complementary assets in marketing and sales serve to maintain the distinct product capabilities.

In contrast, the process firm has distinct capabilities and skills relating to specific manufacturing processes or material process technologies. Process firms are often organized along specific manufacturing operations instead of dedicated product lines. In the automotive industry, process firms tend to represent lower tiered suppliers. The focus of process firms on manufacturing and materials processing means that these firms engage in continuous development and improvement of process efficiency, capacity utilization, and reduction of inventory levels. Figure 1 illustrates the conceptual difference between product and process firms in the automotive component industry.

Examples of product firms in the automotive component industry are Dana, TRW, Gentex and Autoliv. These firms manufacture highly differentiated and complex automotive products such as entire suspension and chassis systems (Dana), engine components, airbags and electronics (TRW), specialized products such as opto-electric rear view mirrors (Gentex) and occupant safety restraint

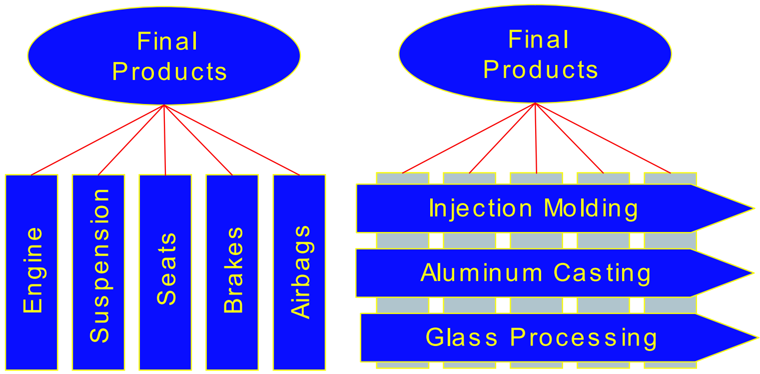


Figure 1: Framework for product- and process-based firms.

systems (Autoliv). As an illustration, Figure 2 depicts Autoliv's product line.

Examples of process firms in the automotive component industry are PPG Industries, Owens Corning, Tower Automotive and Autocam. Their products are typically semi-finished or material-based products such as glass fiber composites, coatings, and foam (PPG and Owens Corning), processed metals such as stamping and roll- or hydro-formed components (Tower Automotive), and precision machined components (Autocam). Figure 3 illustrates Autocam's product line, which serves the automotive, computer and medical equipment industries.

Figure 2: Example of Autoliv's products.

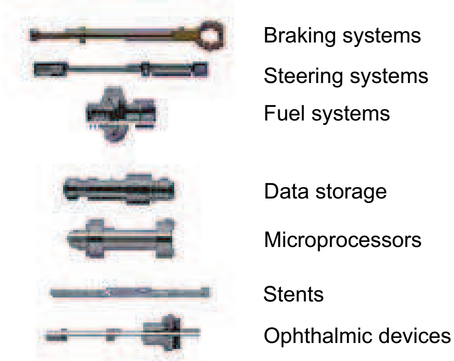


Figure 3: Example of Autocam's products.

Product and process firms tend to differ in the degree of market diversification. The former tend to focus on key customers for which the product has been developed and engineered. In the automotive component industry, automobile manufacturers require close involvement of their largest suppliers in the design and engineering of new product developments. The resulting accumulation of application-specific knowledge limits the possibility for market diversification of product firms. Supplier firms would need to completely redesign their products in order to be able to diversify into markets other than automotive.

In contrast, due to the generic nature of their products, process-based firms are not confined to the market for automotive components, and instead often supply customers in a range of markets in different industries. Consequently, sales of process firms tend to be more diversified across markets relative to product firms. The example of PPG Industries illustrates the highly diversified market presence of a process firm, as the result of efforts to maximize capacity utilization through a broadening of potential product applications[5].

These characteristics are in agreement with the notion that for profit maximizing firms, the type of diversification resulting from a resource endowment depends on the specificity of this endowment. In other words, resources that are end-product specific will lead to related diversification, whereas flexible resources (regarding end products) could lead to unrelated diversification (Chatterjee and Wernerfelt 1991). We have argued that product firms have their capabilities (e.g., intellectual property, R&D, marketing and sales) attached to specific product lines. Therefore, one would expect them to exploit economies of scope in excess resources in related markets (particularly if measured with SIC codes). On the other hand, process firms have their capabilities (e.g., process efficiencies, capacity utilization and reduction of inventory levels) attached to specific processes and, consequently, these capabilities are flexible from the standpoint of end products. Hence, unrelated market diversification could be a profitable exploitation of excess resources in their case.

Chatterjee and Wernerfelt (1991) analyzed the role of three types of resources (physical, intangible, as measured by R&D and marketing expenditures, and financial) on the diversification decision of firms. The first two were thought to be inflexible or specific and associated with related diversification, whereas financial resources were considered flexible and possibly leading to unrelated diversification. While empirical results were supportive of these hypotheses for R&D expenditures and financial resources, there was no statistical support for the physical resources hypothesis. In the present product-process framework, the result for R&D lends credence to the idea that product firms in the automotive supplier industry (which are more R&D intensive) would be better off by exploiting market relatedness. And the lack of significance for the physical assets hypothesis can perhaps be explained as a result of distinct kinds of assets in product and process-based firms. Physical assets in the latter tend to be much less specific than in the former, so that in an uncontrolled random sample of firms the statistical effect would vanish.

Hence, we will test whether related and unrelated market diversification have different consequences for product and process-based firms and their automotive business segments. We can express this with two hypotheses:

Hypothesis 1a: *Related (unrelated) diversification is positively (negatively) associated with the performance of product-based firms and their automotive business segments.*

Hypothesis 1b: *Related and unrelated diversification are positively associated with the performance of process-based firms and their automotive business segments.*

A final comment is relevant regarding the unit of analysis. While the business unit or segment plays a major role in the literature related to the importance of industry and firm effects on profitability, most cross-sectional empirical studies dealing with the relationship between diversification and profitability have taken the firm itself as the primary unit of analysis. However, diversified firms do not compete amongst themselves, rather their business units or segments do

[5]For further information on the characteristics of product- and process based firms in the U.S. automotive supplier industry, see Steinemann (2000).

(Porter 1987). Furthermore, if firms as a whole benefits from economies of scope arising from a strategy of related market diversification, then its individual constituent parts should also benefit, so that business segments in related diversified firms would outperform their peers in undiversified or unrelated diversified firms. Therefore, it is imperative investigate the hypotheses of interest both from the viewpoint of the firm and of its automotive business segments.

Technological diversification and performance

In this paper, we also subscribe to a technological RBV of the firm. We argue that technological capabilities of firms are key to understanding corporate coherence of firms, and explaining the link with superior economic performance. According to this technology-based view of the firm, coherent capabilities in product and process dimensions provide the basis for competitive advantage of firms through synergies and economies of scope among manufacturing activities.

Technological competencies can be located in physical assets, patents and intangibles such as tacit knowledge and organizational routines (Silverman 1999, St. John and Harrison 1999). However, economies of scope originating from technological competencies are potentially different in nature from economies of scope traditionally thought to lead to market diversification. As an illustration, it has been empirically noticed that a firm's technological diversification (viz., in broad terms, the number of technologies it commands) usually anticipates and is larger than its market diversification (Breschi et al. 2003). There are a number of possible reasons for this. First of all, technological diversification does not necessarily lead to product diversification. Firms have to manage many distinct technologies in order to develop and manufacture a single product (Kodama 1986, Breschi et al. 2003) or may simply try to extract higher rents from consumers by adding additional technological complexity to their products (Gambardella and Torrisi 1998). Moreover, firms may hedge against opportunistic behavior (e.g., from suppliers, customers or partners) and against the uncertainties of the future (Pavitt et al. 1989). Finally, they might have to invest in complementary technological knowledge in order to be able to effectively act as systems integrators (Brusoni et al. 2001).

An important empirical finding is the fact that sectoral patterns of technological diversification are heterogenous. This is true not only in the U.S. (Mowery and Nelson 1999), but also in other countries such as Japan Kodama (1986) and the U.K. Pavitt et al. (1989). This means that when studying technological diversification, one ought to recognize the existence of these differences and focus on just one sector.

More recently, interest in technological diversification *per se* and in its relationship with market diversification has been growing. Silverman (1999) uses patent data on 449 4-digit manufacturing industries to quantify a firm's technological resource base. He reports that firms are more likely to diversify into an industry, the more applicable its technological resources are to that industry. In other words, firms diversify to markets where they can exploit economies of scope in technological resources, in accordance to the RBV of the firm. Similarly, Breschi et al. (2003) use data on all firm patents applications to the European Patent Office in 1978–1993 to construct a knowledge-relatedness measure based on patent classification codes. They show that firms are more likely to diversify technologically into knowledge-related fields.

In yet another interesting study, Gambardella and Torrisi (1998) measured technological diversification of thirty two of the largest U.S. and European electronics firms by calculating the

Herfindahl index of each firm's number of patents in 1984–1991 in five sectors: computers, telecommunication equipment, electronics components, other electronics, non-electronic technologies. Downstream (market) diversification was also measured by the Herfindahl index using the number of new subsidiaries, acquisitions, joint-ventures and other collaborative agreements reported in trade journals, for the same five sectors. However, this measure does not capture market relatedness. For example, computers and electronics are different 2-digit industries, whereas telecommunication and electronic components are in the same one. Nevertheless, what really distinguishes their work is that it attempted to quantify the impact of both types of diversification on firm financial performance. Their main findings are that better performance is not only associated with focused (or less diversified) downstream operations or, in other words, focus on their core businesses, but also with increased patent-based technological diversification. They speculate that market focus is necessary due to the difficulty in accumulating downstream (complementary) assets to succeed in new markets, although this could be an artifact due to the lack of a market relatedness measure.

Interestingly enough, these three recent studies rely on patents as proxies for technological capabilities (earlier studies used to focus on even more imperfect proxies such as R&D expenditures). Even discounting the problems with patents, particularly classifications, it is necessary to recognize that patents have limited use outside high-tech industries. Moreover, the codified knowledge embodied in patents usually cannot be readily translated into production and commercialization. The know-how related to technological capabilities in product and process design and manufacturing activities possibly includes a fair amount of tacit knowledge that is not captured by patents and is, therefore, difficult to transfer. Lowe (2003), for instance, discusses the importance of inventors' tacit knowledge and the need for their personal involvement in the context of licensing and commercialization of universities' inventions.

Analogously to the RBV of market diversification, our technological view of the firm implies that automotive business segments that stretch their technological capabilities across different technological areas will tend to, on average, underperform. This will be true for both product- and process-based segments. The assumption here is that valuable manufacturing technological knowledge or know-how is subject to market failure due to transaction costs, externalities and systemic complexities of products and processes (Gambardella and Torrisi 1998). Firms do learn, not only internally, but also through interactions with customers and suppliers (Schroeder, Bates and Juntilla 2002) and this tends to improve efficiency, leading to an under-utilization of current capabilities (St. John and Harrison 1999). Learning also increases the specificity and stickiness of their knowledge base. This path-dependency also means that imitation and substitution are not an option and, therefore, the technological capabilities of the firm assume the characteristic of an strategic asset in the RBV sense. Technological relatedness should emerge as the logic outcome.

Thus, the existence of "excess" technical know-how from its indivisibility and learning (Teece 1982) would prompt the firm to pursue limited technological diversification (in closely related fields), in order to exploit economies of scope in the use of this knowledge, since it cannot contract it out. Diversifying further would lead to a loss of efficiency in this knowledge base, due to its intrinsic specificity, as well as congestions and bottlenecks in information access associated with over-extended engineers (Teece 1980). This, combined with increasing coordination costs, would tend to leave the firm worse off. Hence, our second hypothesis is:

Hypothesis 2: *Technologically diverse product and process-based business segments will underperform in comparison to their more focused or coherent competitors.*

In principle, this hypothesis may seem to be in contradiction with previous results on technological diversification, particularly those reported by Gambardella and Torrisi (1998). Therefore, it is important to stress that this is not necessarily the case. First of all, it is possible that the pattern of technological diversification for the automotive supplier sector simply differs from that of the electronics industry, as discussed by Kodama (1986) and Pavitt et al. (1989).

Secondly and as previously noted, there is gap between what firms know and what they make, so that a proxy for what they know (patents) may not be a good one for what they make and vice-versa. For example, in the large aircraft engine industry, Brusoni et al. (2001) showed that firms invested in and were awarded patents on digital engine control technologies, even though they either never entered production of these control systems since they had arms-length suppliers, or they were divesting their engine control businesses. The point here is that we are interested in technologies and capabilities in the sense of theoretical and practical knowledge underpinning both product design and manufacturing, as well as process operations. This body of knowledge is dynamic, and distinct from that embedded in patents, as noted by Teece (1980) and illustrated by the literature on learning curves (Argote and Epple 1990).

This idea is similar to that presented by Schroeder et al. (2002) who argue that learning generates proprietary processes and equipment, both subject to causal ambiguity and market failure. These two idiosyncratic resources then lead to superior *manufacturing* performance. Using qualitative data from a survey of 164 manufacturing plants in five countries and three different industries (electronics, machinery, and, curiously, the automobile component suppliers), they find empirical support for their theory.

Following the same line of inquiry, St. John and Harrison (1999) attempt to verify if technological or manufacturing relatedness at the firm level leads to better performance. They use expert opinion to classify business segments as belonging to tightly, loosely linked, or unrelated manufacturing firms, based on similarities in raw material, science, technology, and resource conversion processes. Segments in tightly or loosely linked firms are supposed to have better performance than segments in single-business of manufacturing-unrelated firms. They also use public information and structured interviews to determine whether firms are explicitly engaged in synergy creation through technological resource sharing. Although they find out that high-performing firms were indeed trying to create synergy, the empirical results were not supportive of the manufacturing relatedness-performance hypothesis. However, as they promptly recognize, the analysis could be limited by the lack of a market relatedness measure, possibly confounding results.

Hence, it is important to recognize that market and technological diversification are somewhat intertwined. Technological capabilities and specialized know-how have been shown to influence the expansion of operations to other markets (Teece 1980, Silverman 1999). Managers also have to make technological and end products choices in the same time frame (Teece 1982). In the present work, we attempt to avoid these complications by measuring technological diversification in detail at the automotive segment level only, while controlling for possible synergies arising from market diversification at the firm level.

METHODOLOGY

Data

The subject of the analysis, the automotive component industry, needs to be carefully described. It is defined as firms primarily engaged in manufacturing of semi-finished and finished automotive components. The definition excludes suppliers of raw materials, tool manufacturers, suppliers of instrumentation and computer services, testing services, software developers, pure R&D companies, pure manufacturers of components for trucks and other transportation equipment, and pure automotive aftermarket firms.

The previous decade was chosen as the time period for the analysis. This period covers approximately one full economic cycle of the automotive industry (Steinemann 2000). Reporting requirements for financial disclosures of business segment information has changed in 1998, and therefore the ten-year period from 1988 to 1997 was chosen to exclude the effect of these reporting changes.

Data on products and processes of firms was taken from company annual reports (10-K) filed with the Securities Exchange Commission (SEC). Unfortunately, these reports are only available electronically after 1993, so detailed data on products and processes capabilities in this study covers the period from 1993 to 1997. Financial data was taken from COMPUSTAT™, so that each firm can have a total of 10 distinct reported business segments. To include as many firms as possible in the analysis, a broad list containing over 650 firm names was compiled from multiple sources[6], and this list was then narrowed down to meet the criteria of the industry definition.

Our panel encompasses only U.S. registered, public companies. A firm was included in the data set, if it had at least one business segment whose sales to the automobile industry represented a minimum of 50% of its total sales. Data were excluded when a firm had less than $50 million in sales in any given year, and for firm segments with less than $20 million in sales. This data set totals 88 firms and 94 business segment in the ten-year period, indicating that only 6 firms have more than one automotive business segment. After dropping invalid or missing observations, this panel cover approximately 600 segment-years and $120 billion of annual sales. According to other sources, the size of the automotive component industry in the United States is about $150-$250 billion, depending on how far lower tier suppliers are included. Please note that when testing Hypothesis 2, we have to use a 5-year panel with half of this size because data on technological capabilities are constrained to the 1993–1997 time frame.

The largest bias in the selection of companies probably originates from the exclusion of private and international companies, batteries and raw materials suppliers, and subsidiaries of automobile manufacturers. The latter deserve special mention. General Motors automotive parts division is believed to be the world's largest automotive component manufacturer. This division, Delphi Automotive, has been quoted as a separate public company only since 1998. Ford Motor does not publish separate financial information for its component division (Visteon). Chrysler has divested

[6] Firms in COMPUSTAT™ with at least one business segment representing SIC code 3714 (Motor Vehicle Parts & Accessories) and/or business segments having an automotive manufacturer as primary business segment customer; firms listed in the 1998 Market Data Book of Automotive News, and firms listed in the Automotive Engineering International 8th Annual Product Sourcing Guide, North America (1999).

most of its component manufacturing operations and does not publish separate financial information for the remaining component division.

A comment regarding mergers and acquisitions in the industry is necessary. There were 3 cases in the 10-year period when a firm in our panel was acquired by another firm in the data set, all happening in 1996. We deal with this situation by censoring data for the target firm after 1996 and normally reporting the data for the acquirer. This is not expected to introduce any bias.

Finally, it is important to highlight that the availability of a panel will increase the confidence in the results, since the diversification-performance relationship might not be time-invariant. Particularly, the benefits and costs of a particular diversification strategy are not thought to arise in short time spans (Gambardella and Torrisi 1998).

Measures

Dependent variables

Initially, we will investigate in our sample the hypothesis that diversification into unrelated markets is beneficial only for process firms, whereas related diversification is positively associated with performance for both types of firms (Hypothesis 1).

The dependent variable is the measure of economic performance at the firm level. Although there are some problems with the use of accounting-based measures for this purpose, such as not providing for the capitalization of certain activities (e.g., R&D) and ignoring inflation (Fisher and McGowan 1983), they constitute the focus of most Management research. In their defense, it is possible to argue that managerial decision making as well as analysis and academic research have been consistently performed using profitability data from financial statements (Bettis 1981, Ramanujam and Varadarajan 1989). More recently, the interest in adopting market-based measures has been growing, since they include expectations of future returns, adjustments for risk and minimize biases related to managerial discretion, tax laws and accounting conventions (Montgomery and Wernerfelt 1988, Palich et al. 2000).

In any case, we avoid siding with any particular measure and follow the advice given by Ramanujam and Varadarajan (1989) of relying on multiple measures to attain robustness of results. We use two different accounting-based measures: return on assets (ROA, the ratio between operating income after depreciation and total assets) and return on sales (ROS, the ratio between operating income after depreciation and total sales). We also include Tobin's q (the ratio between a firm's market value and the replacement value of its productive assets), a measure combining capital market data with accounting data. By taking into account the market value of the firm, q contains an intrinsic adjustment for risk. If for a competitive firm q is expected to be close to unit, for a firm earning Ricardian rents on strategic assets (and assuming no monopoly rents) q should exceed unit. This happens because the market capitalizes these rents and, to the extent that the total value strategic assets is not captured by its book replacement cost, the firm value will exceed this cost (Lindenberg and Ross 1981).

As we have previously alluded to, firms do not compete against each other. Rather, their business segments do. Therefore, we want to test Hypothesis 1 at the segment level as well. If related market diversification is superior because of economies of scope originating from resource sharing among business segments, then these segments should outperform their counterparts in firms following different diversification strategies. Performance is now measured with ROA and ROS only at this level, since business segments do not have a market value. These two segment-level measures are also used to test Hypothesis 2.

Independent variables

Market diversification

The independent variables of interest at the firm level are those related to market diversification. This is calculated with the entropy index (Jacquemin and Berry 1979), based on the assignment of SIC codes to all of the firm's business segments (not only the automotive segment). Despite the inherent problems in the use of SIC codes to infer diversification, such as the fact that it ignores certain aspects of product relatedness (e.g. vertical integration and input or output complementarities between industries) and that differences between SIC codes do not translate directly into distance between markets, one can take solace in the high degree of correspondence found between continuous SIC-based measures of diversification and Rumelt's categories (Montgomery 1982).

A major advantage of the entropy index over other metrics such as the Herfindahl is that besides being sensitive to the presence of small segments it can be split into additive components of related and unrelated diversification (Jacquemin and Berry 1979, Palepu 1985). Related diversification is defined as that arising from operations in different 4-digit markets within the same 2-digit industry. That is, for each 2-digit industry where a firm operates, its related diversification measure is $DR_v = \sum_{u \in v} s_{u,v} \ln(1/s_{u,v})$, where $s_{u,v}$ is the share of sales of business segment u (at the 4-digit level) to total sales of the firm at the 2-digit industry level v. The total related diversification for a firm can be aggregated as $DR = \sum_v DR_v s_v$, where s_v is the share of sales in the 2-digit industry v to total sales of the firm.

The unrelated component of diversification is given by $DU = \sum_v s_v \ln(1/s_v)$, i.e., it is the degree of diversification in different 2-digit defined industries. As is demonstrated by Palepu (1985), a firm's total diversification can then be quantified as the sum of its related and unrelated parts: $DT = \sum_u s_u \ln(1/s_u) = DR + DU$, where s_u is the share of sales in the 4-digit segment u to total firm sales.

Product and process differences

Due to the distinct corporate logics followed by product- and process-based firms discussed in the previous section, controlling for this characteristic is essential. *PROC* is then a dummy variable assuming the value 1, if the firm is classified as process-based, or 0, if otherwise. This categorization is primarily based on self-reported technological capabilities and their organization within the firm. This information is contained in the annual 10-K reports filed with the SEC. Table 1 presents all the criteria employed in this classification. In the automotive supplier industry, the focus on products or processes happen to be quite separable. And although hybrid forms of product / process focus may exist in large firms that have acquired capabilities in a large number of products and processes over a long time, only six firms were found to have an ambiguous focus. Approximately, 35% of firms have been classified as process-based ones.

Since all firms have a measure of related (DR) and unrelated (DU) market diversification, the interaction terms $PROC \times DR$ and $PROC \times DU$ are introduced to capture the expected differences between process and product firms regarding their abilities to exploit different diversification

Definition and primary criteria	
Product firm	**Process firm**
Firm has distinct capabilities relating to individual products or product lines	Firm has distinct capabilities relating to specific manufacturing processes or materials processing
Secondary criteria	
Firm is organized along individual product lines	Firm is organized along manufacturing processes
Firm is engaged in research and product development, and the protection of intellectual property relating to products	Firm is engaged in on-going process development and improvements, and occasional protection of intellectual property relating to processes and materials
Products are highly differentiated, specialized, or complex	Products are generic, semi-finished, or material-based
Pre-manufactured parts represent a large percentage of purchased inputs	Raw materials represent a large percentage of purchased inputs

Table 1: Criteria used in conjunction with SEC 10-K reports to classify firms and their automotive business segments as either product- or process-based.

strategies. With these interactions, we expect the coefficient of *DR* (directly measuring related diversification for product firms) to be positive, whereas the one for *DU* is expected to be negative, as predicted by Hypothesis 1a. Hypothesis 1b predicts that the sum of the coefficients for *DR* and $PROC \times DR$ is positive and the sum of those for *DU* and $PROC \times DU$ is positive as well. This should be true at both levels of analysis if segments are also benefitting from synergy creation within the firm.

Note that segments are classified as product- or process-based in the same way firms are. Although there is no reason not to have a product-based segment in a process-based firm or vice-versa, it happens that in our sample their classifications coincide. All product segments are in product-based firms and all process segments in process-based firms, so that the same variable *PROC* can be used at both levels of analysis interchangeably.

Technological diversification

Since the identification of individual technologies is only available for the automotive business segment, Hypothesis 2 is only tested at this level (and for the last five years of the sample). $TECH\_DIV$ is our measure of technological diversification

In the present paper, according to the framework for classifying firms as product- or process-based presented in the theory section, technological capabilities are identified within a 3-level hierarchical classification of products and processes. This classification scheme is presented in Appendix B and is based on criteria involving technological interrelationships of products and processes. Two products are related if they are placed in the same 3-digit branches (second level) of the classification tree. Products and processes are grouped according primarily to the proximity in manufacturing technologies. Technical and engineering literature on automotive components served as a guideline for establishing the classification scheme (see Steinemann (2000) and references therein). Appendix A introduces all the criteria used in the construction of the classification

For validation purposes, the classification was presented to two experts in the field of automotive products and processes. Once it was validated, we turned to the 10-K reports to identify whether a firm's automotive segment was active in each one of the third level technologies, in both product and process dimensions. Companies were found to command each of these technologies only if they were explicitly reported in the 10-K documents. Nothing was assumed.

$TECH\_DIV$ was then calculated using the entropy index based on the ratio of the number of technological capabilities (in which the automotive business segment is active) in each of the second level (3-digit) categories (e.g., 011 – structural components or 111 – assembly) to the total number of active capabilities identified for the segment. Naturally, the sample was split and depending on whether the segment was product- or process-based, the respective scheme was employed. Breschi et al. (2003) have noted that despite the evidence that firms exhibit coherence in their technological capabilities, a lack of rigorous conceptualization and measurement of this coherence is prevalent in the literature. Here, we make an explicit attempt to address this issue in the automotive industry with the $TECH\_DIV$ metric based on our hierarchical classification.

Formally, $TECH\_DIV = \sum_c s_c \ln(1/s_c)$, where s_c is the share of the automotive segment's technologies in each of the 3-digit categories. This is analogous to the unrelated market diversification measure DU. Although, in principle, it would be possible to calculate a related component of technological diversification analogous to DR within each 3-digit category, this was not done here[7]. Hence, $TECH\_DIV$ measures diversification across second level categories, but not within them. According to Hypothesis 2, the coefficient for $TECH\_DIV$ is expected to be negative.

It is also important to acknowledge that the type of classification developed and employed in this paper is not entirely new. Monteverde and Teece (1982), for instance, used a somewhat similar classification based on expert evaluation of technical relatedness of automotive component to test hypotheses regarding transaction costs and vertical integration. Moreover, in the case of product-based segments where capabilities are not explicit in the hierarchy, the classification scheme is primarily based on the underlying technologies going into the products. Therefore, we argue that this will also be a good proxy for technological diversity. Firms choose to manufacture components for which they have both the technical know-how and the understanding of the integration requirements with the final product, the automobile. Thus, we feel comfortable in arguing that although the hierarchical-based technological diversification measure employed in this paper is not perfect, it complements patent-based measures, distinguishing between what firms know and what they make. It can also be adapted to measure diversity in technological capabilities for additional industries where patent-based measures are not an option.

Control variables

To control for firm size, we use the variable sales in log form, $\ln(SALES)$. But since we argued in the theoretical section that process firms are better able to exploit economies of scale, $\ln(SALES)$ is also interacted with $PROC$ to account for this difference. $RISK$ measures the standard deviation of the accounting measures (ROA or ROS) during the 10-year period. This covariate is included because financial theory predicts that higher risk should be related to higher returns[8] (Bettis and Mahajan 1985). DIV_GEO measures the geographical diversification of the firm in the three

[7] There is a lot of variability in the number of third-level capabilities within each second-level categories. For process-based segments, for example, many of the second-level categories contain only one technological capability. This prevents a reasonable measurement of related technological diversification.

[8] Note that when performance is measured with Tobin's q, $RISK$ is omitted from the model.

largest world markets, North America, Asia and Europe, and is based on the Herfindahl index: $DIV\_GEO = 1 - \sum_{k=1}^{3} s_k^2$, where s_k is the share of firm's sales in one of the three markets. Since firms that have sales in more than one world market are likely to better cope with downturns in localized economic cycles, this coefficient is expected to be positive.

SALGR measures the firm's yearly sales growth and is included because growth is thought not only to constrain performance (Bettis and Mahajan 1985), but also to be correlated with diversification in the product life cycle paradigm, i.e., firms located in stable or declining markets are more prone to diversify than firms in high-growth markets (Christensen and Montgomery 1981). Finally, $CAPEX$ controls for firm-level capital expenditures[9].

Testing Hypotheses 1 and 2 for the automotive business segments means that $\ln(SALES)$ and $CAPEX$ are measured at this level. So are *RISK* and *SALGR*, even though it is not obvious that the rationale for including *RISK* at the firm level necessarily carries over to the business segment, and in we still want to control for sales growth at the firm level due to its potential correlation with *DR* and DU. A final control at the segment level is a measure of customer concentration ($CUSTC$) based on the Herfindahl index of sales to General Motors, Ford and Chrysler. This variable is supposed to account for customer power, according to the five forces model (Porter 1980). Hence, $CUSTC$ should have a negative impact on the performance of the automotive business segment.

In all regressions, at all levels, year dummies are also included to control for time-specific shocks to firm performance. Table 2 presents the correlation coefficients and descriptive statistics for all variables included in at both firm and business segment levels. It also includes correlation coefficients for the 5-year sub-sample at the segment level, which will be used to address Hypothesis 2.

Statistical method and analysis

The most efficient estimator for panel data is the random effects estimator which takes account of variation both within and between cross-sectional units. Unfortunately, a Hausman test rejected the assumptions necessary for the use of a random effects estimator. A second-best solution would be to use a fixed effects estimator. However, fixed effects is not indicated here either, since it would wipe out time-invariant explanatory variables. A particular concern is that the market and especially the technological diversification measures are found to be particularly stable across the years, as in previous studies Breschi et al. (2003). Therefore, fixed effects could lead to imprecise estimates (Wooldridge 2001).

Thus, we have opted for a pooled OLS estimator, with heteroscedastic panel-corrected standard errors (PCSE). In principle, a feasible generalized least squares (FGLS) estimator could also have been used. However, Beck and Katz (1995) have demonstrated that FGLS in the presence of heteroscedasticity and serial correlation produces standard errors whose variability is highly underestimated, leading to overconfidence in the estimates. The problem arises from the estimation of the error covariance matrix. Ours is an unbalanced panel with randomly dispersed missing variables, something that does not introduce any bias but makes this matrix estimation imprecise. This would contribute to the underestimation of the variability of the parameters standard errors.

[9] Research and development expenditures would represent another desirable control variable, but it is not available for many firms in the data set, and was therefore not included.

Full sample (10 yrs)				Correlation coefficients																		
Variables	Observ.	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. ROA	753	0.108	0.069																			
2. ROA†	631	0.127	0.111	0.739																		
3. ROS	778	0.082	0.055	0.838	0.6298																	
4. ROS†	655	0.074	0.110	0.690	0.762	0.790																
5. Tobin's q	628	1.534	0.886	0.525	0.463	0.618	0.515															
6. *PROC*	940	0.351	0.478	-0.101	-0.201	-0.110	-0.131	-0.212														
7. *DR*	783	0.112	0.224	-0.001	-0.034	0.121	0.031	0.021	-0.122													
8. *DU*	783	0.399	0.454	-0.162	0.127	-0.096	-0.012	-0.124	-0.268	0.191												
9. ln(*SALES*)	783	6.323	1.865	-0.131	0.049	-0.059	-0.005	-0.146	-0.422	0.412	0.559											
10. ln(*SALES*)†	655	5.769	1.657	-0.108	0.072	-0.060	0.059	-0.118	-0.401	0.209	0.330	0.916										
11. *RISK* (ROA)	900	0.043	0.035	0.189	0.089	0.043	0.044	0.225	-0.007	-0.195	-0.355	-0.506	-0.460									
12. *RISK* (ROA)†	870	0.056	0.041	0.204	0.187	0.085	0.006	0.205	-0.201	0.019	-0.116	-0.265	-0.329	0.722								
13. *RISK* (ROS)	940	0.028	0.025	0.141	0.055	0.071	0.058	0.329	-0.083	-0.154	-0.286	-0.470	-0.439	0.713	0.467							
14. *RISK* (ROS)†	910	0.043	0.087	0.092	-0.071	0.090	-0.150	0.210	-0.128	-0.034	-0.207	-0.342	-0.385	0.358	0.607	0.527						
15. *DIV_GEO*	782	0.693	0.303	0.114	0.000	0.014	-0.014	0.073	0.395	-0.217	-0.297	-0.635	-0.604	0.365	0.163	0.254	0.167					
16. *SALGR*	687	0.129	0.313	0.104	0.009	0.121	0.062	0.157	0.018	-0.132	-0.195	-0.222	-0.172	0.128	0.089	0.233	0.209	0.118				
17. *SALGR*†	560	0.236	0.974	0.008	-0.061	0.064	-0.038	0.078	0.019	-0.021	-0.022	-0.152	-0.179	0.037	0.089	0.102	0.226	0.056	0.619			
18. *CAPEX*	762	0.058	0.044	0.105	-0.049	0.344	0.110	0.226	0.141	-0.005	-0.220	-0.286	-0.264	0.003	0.037	0.019	0.246	0.108	0.117	0.167		
19. *CAPEX*†	606	0.077	0.161	0.015	-0.150	0.133	-0.295	0.129	-0.020	0.070	-0.097	-0.152	-0.229	0.001	0.200	0.007	0.456	0.055	0.085	0.234	0.486	
20. *CUSTC*†	652	0.144	0.181	-0.043	-0.076	-0.097	-0.045	0.017	0.357	-0.152	-0.234	-0.245	-0.144	0.051	-0.151	-0.032	-0.160	0.331	0.047	-0.038	0.060	-0.062
5-year sample (1993–1997)																						
1. ROA†	364	0.143	0.113																			
2. ROS†	380	0.091	0.057	0.784																		
3. *PROC*	470	0.351	0.478	-0.208	-0.152																	
4. *TECH_DIV*	257	1.022	0.569	-0.011	-0.217	-0.335																
5. *TECH_COH*	257	0.419	0.269	0.047	0.290	0.280	-0.931															
6. *DR*	433	0.090	0.204	0.063	0.171	-0.077	0.007	0.001														
7. *DU*	433	0.364	0.432	0.163	0.037	-0.136	0.198	-0.202	0.268													
8. ln(*SALES*)†	380	5.900	1.611	0.045	0.047	-0.354	0.505	-0.455	0.316	0.248												
9. *RISK* (ROA)†	435	0.056	0.041	0.446	0.297	-0.104	-0.204	0.210	0.007	-0.018	-0.273											
10. *RISK* (ROS)†	455	0.043	0.087	0.131	0.151	-0.046	-0.352	0.423	-0.005	-0.097	-0.284	0.595										
11. *SALGR*	414	0.151	0.274	-0.074	-0.006	0.006	-0.169	0.147	-0.159	-0.239	-0.052	-0.006	0.023									
12. *SALGR*†	352	0.247	1.032	-0.067	0.039	-0.021	-0.209	0.172	-0.089	-0.120	-0.058	0.017	0.031	0.880								
13. *CAPEX*†	358	0.067	0.056	-0.084	0.218	0.064	-0.389	0.410	0.085	-0.115	-0.208	-0.013	0.180	0.143	0.193							
14. *CUSTC*†	378	0.129	0.155	-0.116	-0.145	0.218	-0.196	0.106	-0.204	-0.277	-0.161	-0.152	-0.158	0.140	0.094	0.051						

† Segment-level variables

Table 2: Correlation coefficients and descriptive statistics of variables that will be used in testing Hypotheses 1 and 2, for both 10 and 5-year samples.

Hence, to be on the conservative side, we employ a pooled OLS estimator. First, we attempt to eliminate serial autocorrelation in the errors within panels through the use of a lagged dependent variable. A one-period lagged dependent variable also has the advantage of controlling for unobserved firm or segment heterogeneity. We then use the residuals of an OLS regression to test our models for any residual autocorrelation. In all of our models, the autocorrelation left is neither large nor statistically significant, attesting that the models are dynamically complete (Beck and Katz 1996, Wooldridge 2001). But OLS in the presence of pure heteroscedasticity is still not as efficient as FGLS. OLS standard errors therefore need to be corrected. The PCSE strategy employs the residuals from the pooled OLS regression to account for the remaining heteroscedasticity in the panel structure and correct the parameters standard errors. Monte Carlo simulations have shown that inefficiencies in pooled OLS estimates are minimal and PCSE perform very well in many different situations (Beck and Katz 1995).

RESULTS

Hypothesis 1 at the firm level

Table 3 presents the results of the test of Hypothesis 1 at the firm level. Model 1F[10] includes only the independent variables and year dummies (whose parameters are not reported) but without the interaction between process dummy and the market diversification variables. Therefore *DR* and *DU* measure diversification for both types of firms. As can be seen, results are in agreement with those in the literature: related diversification is beneficial, whereas unrelated negatively impacts performance.

Model 2F is basically the same as 1F, but with the two interaction terms $PROC \times DR$ and $PROC \times DU$ added. Table 3 shows that the interaction parameters are not statistically significant. However, introducing the control variables in Model 3F changes this somewhat.

The parameters for *DR* and *DU* in Model 3F directly provide the partial effects of related and unrelated diversification on product firms. As can be seen, the parameters for *DR* are always positive, and statistically significant when ROA and ROS are used to measure performance. For *DU*, only when ROS is the performance measure is the parameter significant and in this case also positive. Partial effects for process firms can be found by plugging $PROC = 1$ and adding the respective coefficients. Note that statistical significance has to be tested *a posteriori*. Doing this, we see that for process firms the coefficients for *DR* are neither stable in terms of sign nor close to being statistically significant. Moreover, unrelated diversification is negatively associated with performance with two partial effetcs (-0.0226 and -0.0148) attaining significance at the 10% level for ROA and ROS, respectively.

[10] In addition to ROA and ROS, we also estimated the firm-level model using an alternative accounting-based measure: return on invested capital. ROIC is defined as the ratio between income before extraordinary items and the sum of total common equity, short- and long-term debt. Results were in essence comparable to those reported.

	Firm-level								
	Model 1F			Model 2F			Model 3F		
	ROA	ROS	Tobin's q	ROA	ROS	Tobin's q	ROA	ROS	Tobin's q
Intercept	0.0309***	0.0318***	0.4907***	0.0310***	0.0313***	0.5007***	0.0417*	0.0098	0.4620
	(0.0090)	(0.0069)	(0.1573)	(0.0092)	(0.0071)	(0.1587)	(0.0228)	(0.0136)	(0.3638)
$PERFORMANCE_{t-1}$	0.7374***	0.6664***	0.7820***	0.7361***	0.6660***	0.7810***	0.7193***	0.6813***	0.7378***
	(0.0497)	(0.0488)	(0.1163)	(0.0499)	(0.0489)	(0.1159)	(0.0526)	(0.0389)	(0.1290)
$PROC$	−0.0118***	−0.0071**	−0.1155***	−0.0118**	-0.0060	−0.1353**	−0.0558***	−0.0288**	−0.5673**
	(0.0041)	(0.0030)	(0.0391)	(0.0056)	(0.0041)	(0.0585)	(0.0212)	(0.0141)	0.2526
DR	0.0011	0.0183***	0.0589	-0.0018	0.0196***	0.0684	0.0141*	0.0295***	0.1750
	(0.0073)	(0.0059)	(0.0855)	(0.0072)	(0.0067)	(0.1071)	(0.0084)	(0.0073)	(0.1268)
DU	−0.0086**	−0.0058*	−0.0888*	−0.0080*	-0.0052	−0.1089*	0.0015	0.0063**	−0.0266
	(0.0041)	(0.0031)	(0.0469)	(0.0046)	(0.0036)	(0.0591)	(0.0044)	(0.0032)	(0.0498)
$PROC \times DR$	–	–	–	0.0145	-0.0042	-0.0787	-0.0161	-0.0174	-0.2345
	–	–	–	(0.0253)	(0.0144)	(0.1179)	(0.0272)	(0.0155)	(0.1480)
$PROC \times DU$	–	–	–	-0.0047	-0.0024	0.0875	−0.0242*	−0.0211**	-0.0711
	–	–	–	(0.0111)	(0.0070)	(0.0782)	(0.0131)	(0.0091)	(0.1024)
$\ln(SALES)$	–	–	–	–	–	–	-0.0034	-0.0015	-0.0383
	–	–	–	–	–	–	(0.0023)	(0.0015)	(0.0284)
$PROC \times \ln(SALES)$	–	–	–	–	–	–	0.0085**	0.0049**	0.0729*
	–	–	–	–	–	–	(0.0037)	(0.0025)	(0.0384)
$SALGR$	–	–	–	–	–	–	0.0149	0.0338***	0.0177
	–	–	–	–	–	–	(0.0093)	(0.0079)	(0.0757)
$CAPEX$	–	–	–	–	–	–	−0.0900**	0.0344	0.5533
	–	–	–	–	–	–	(0.0462)	(0.0355)	(1.0558)
$RISK$	–	–	–	–	–	–	0.0692	0.1226	–
	–	–	–	–	–	–	(0.1480)	(0.0962)	–
DIV_GEO	–	–	–	–	–	–	0.0094	0.0072	0.1004
	–	–	–	–	–	–	(0.0076)	(0.0055)	(0.0848)
Observations	607	628	487	607	628	487	593	618	473
R^2	0.5906	0.5899	0.6471	0.5910	0.5900	0.6475	0.6063	0.6461	0.6542
Wald χ^2	303.57***	357.19***	247.65***	311.86***	363.53***	269.98***	398.21***	708.00***	357.36***
* significant at 10%, ** at 5%, *** at 1%, standard errors in parenthesis									

Table 3: Results for the test of Hypothesis 1 at the firm level.

From these results[11], one can conclude that there is only weak support for Hypothesis 1a at the firm level. While related diversification has a positive impact on performance, there is no evidence that unrelated diversification is hurting product firms. Moreover, the magnitude of the influence is small. Considering the partial effect of *DR* on ROS, which is the strongest, it is possible to calculate that an increase in the firm's *DR* by one standard deviation would increase its return by only 0.6%.

Furthermore, there is no support for Hypothesis 1b. Market relatedness does not seem to influence the performance of process firms. And contrary to Hypothesis 1b, unrelated diversification was found to hurt their performance. In the ROA case, an increase in *DU* of one standard deviation decreases the return by approximately 1%.

Model 3F reveals important differences in terms of economies of scale accruing to product and process firms. For product firms, the parameters for $\ln(SALES)$ can be obtained directly from Table 3. The three are negative, though not significant. In contrast, for process firms, adding the coefficients yields 0.0052^{*}, 0.0033 and 0.0346 for the respective performance measures. While only the first one is significant at the 10% level, the other two are pretty close to that level as well, suggesting that process firms do indeed benefit from scale economies.

Table 3 also shows that process firms tend to underperform their product peers, as denoted by the *PROC* coefficients. In Model 3F, due to the interaction terms, *PROC* represents the average difference between single-business product and process firms, i.e., when $DR = DU = 0$, and at a zero level of sales, which is uninteresting. The model was then re-estimated at the mean values of sales as well as related and unrelated diversification. This leads to *PROC* coefficients of -0.0558^{***}, -0.0288^{**} and -0.5673^{**}, for ROA, ROS and Tobin's q, respectively. Thus, it seems that the performance difference between product and process firms is valid throughout diversification strategies[12].

Hypothesis 1 at the segment level

Now, we turn to test Hypothesis 1 at the automotive business segment level. Table 4 presents the results. Once again Model 1S and 2S include only the independent variables and year dummies. The distinction between them is only the presence of the interaction term between the process dummy and market diversification varibles. Both models seem to suggest that the automotive business segments are neither benefitting (that is, no synergies) nor being hurt by the diversification strategies of their parent companies.

Model 3S includes all control variables. Note that we are also controlling for the standard deviations of returns at the segment level[13] with *RISK*.

[11] We estimated another model not reported here with R&D expenditures as an additional covariate. The number of observations was considerably reduced due to an overall lack of R&D data and, therefore, standard errors increased. But overall, it had no impact on the overall parameter estimates.

[12] Results available from the authors show that the difference in performance between product and process firms grow when both *DR* and *DU* increase, irrespective of the level of sales.

[13] Excluding this covariate has no effect on the results. An additional model also not reported here also included a control for sales growth at the segment level. This covariate was not significant nor did its inclusion alter any of the other estimates.

	Segment-level					
	Model 1S		Model 2S		Model 3S	
	ROA	ROS	ROA	ROS	ROA	ROS
Intercept	0.0179^{*}	0.0460^{***}	0.0184^{*}	0.0453^{***}	0.0087	0.0388^{***}
	(0.0105)	(0.0067)	(0.0108)	(0.0068)	(0.0256)	(0.0137)
$PERFORMANCE_{t-1}$	0.8280^{***}	0.3880^{***}	0.8260^{***}	0.3870^{***}	0.8022^{***}	0.6549^{***}
	(0.0467)	(0.0366)	(0.0474)	(0.0363)	(0.0492)	(0.0353)
PROC	-0.0168^{***}	-0.0123^{***}	-0.0180^{***}	-0.0109^{**}	-0.0710^{***}	-0.0740^{***}
	(0.0050)	(0.0038)	(0.0065)	(0.0045)	(0.0251)	(0.0158)
DR	-0.0053	0.0129	-0.0098	0.0069	-0.0035	0.0117
	(0.0119)	(0.0097)	(0.0144)	(0.0114)	(0.0134)	(0.0077)
DU	0.0014	0.0000	0.0016	0.0025	0.0121^{**}	0.0063^{**}
	(0.0054)	(0.0042)	(0.0063)	(0.0046)	(0.0057)	(0.0031)
$PROC \times DR$	–	–	0.0191	0.0322	0.0055	0.0054
	–	–	(0.0245)	(0.0206)	(0.0246)	(0.0163)
$PROC \times DU$	–	–	-0.0026	-0.0153	-0.0257^{*}	-0.0257^{***}
	–	–	(0.0125)	(0.0098)	(0.0131)	(0.0091)
$\ln(SALES)^{\dagger}$	–	–	–	–	-0.0028	-0.0042^{***}
	–	–	–	–	(0.0029)	(0.0016)
$PROC \times \ln(SALES)^{\dagger}$	–	–	–	–	0.0122^{***}	0.0132^{***}
	–	–	–	–	0.0042	(0.0027)
SALGR	–	–	–	–	0.0183^{*}	0.0349^{***}
	–	–	–	–	(0.0103)	(0.0081)
$CAPEX^{\dagger}$	–	–	–	–	-0.0004	0.0543^{***}
	–	–	–	–	(0.0171)	(0.0163)
$RISK^{\dagger}$	–	–	–	–	0.2201^{*}	0.0248
	–	–	–	–	(0.1305)	(0.0542)
$CUSTC^{\dagger}$	–	–	–	–	-0.0127	-0.0115
	–	–	–	–	(0.0150)	(0.0091)
Observations	540	560	540	560	538	539
R^2	0.7152	0.5711	0.7154	0.5736	0.7350	0.6927
Wald χ^2	416.86^{***}	229.68^{***}	435.37^{***}	248.62^{***}	549.81^{***}	765.13^{***}

† Segment-level covariates
* significant at 10%, ** at 5%, *** at 1%, standard errors in parenthesis

Table 4: Results for the test of Hypothesis 1 at the segment level.

Results point once again for differences in economies of scale in product and process segments. Whereas the formers seem to suffer from “diseconomies” of scale (-0.0028 for ROA and -0.0042^{***} for ROS), the latter enjoy the benefits of scale economies (0.0094^{***} and 0.0090^{***}, respectively). Model 3S still shows that process segments, just like their corporate parents underperform on average. The parameters for *PROC* at the means of the variables with which it interacts demonstrate that returns for process segments are lower by -0.0100^{**} and -0.0077^{**}, respectively.

The most puzzling results, though, come from the diversification variables. For process segments, performance is not improved by related diversification at the firm level. And there is indication that it is worsened by unrelated diversification according to the *DU* parameters (-0.0136 for ROA and -0.0194^{**} for ROS). This particular result is contrary to Hypothesis 1b, but at least in agreement with previous research in the field. In contrast, for product segments, we find that while relatedness is not associated with changes in performance, unrelated diversification improves the

	Segment-level					
	Model 4S		Model 5S		Model 6S	
	ROA	ROS	ROA	ROS	ROA	ROS
Intercept	0.0422**	0.0573***	0.0417**	0.0581***	0.0602*	0.0450**
	(0.0174)	(0.0125)	(0.0174)	(0.0125)	(0.0371)	(0.0186)
$PERFORMANCE_{t-1}$	0.9051***	0.6067***	0.9028***	0.5974***	0.8940***	0.8428***
	(0.0585)	(0.0892)	(0.0602)	(0.0903)	(0.0627)	(0.0560)
$PROC$	-0.0055	-0.0124**	-0.0043	-0.0108*	-0.0322	-0.0278
	(0.0077)	(0.0051)	(0.0101)	(0.0058)	(0.0421)	(0.0228)
$TECH\_DIV^{\dagger}$	-0.0091	-0.0111**	-0.0092	-0.0114**	-0.0163*	-0.0121***
	(0.0078)	(0.0048)	(0.0078)	(0.0048)	(0.0087)	(0.0048)
DR	-0.0043	0.0103	-0.0067	0.0033	-0.0039	0.0049
	(0.0205)	(0.0117)	(0.0240)	(0.0129)	(0.0236)	(0.0102)
DU	0.0081	0.0055	0.0098	0.0086	0.0073	0.0010
	(0.0090)	(0.0051)	(0.0112)	(0.0061)	(0.0115)	(0.0047)
$PROC \times DR$	–	–	0.0166	0.0474	-0.0286	-0.0132
	–	–	(0.0362)	(0.0336)	(0.0384)	(0.0236)
$PROC \times DU$	–	–	-0.0084	-0.0182	-0.0073	-0.0067
	–	–	(0.0181)	(0.0123)	(0.0178)	(0.0098)
$\ln(SALES)^{\dagger}$	–	–	–	–	0.0005	0.0003
	–	–	–	–	(0.0045)	(0.0021)
$PROC \times \ln(SALES)^{\dagger}$	–	–	–	–	0.0057	0.0048
	–	–	–	–	(0.0066)	(0.0037)
$SALGR$	–	–	–	–	0.0046	-0.0107
	–	–	–	–	(0.0160)	(0.0096)
$CAPEX^{\dagger}$	–	–	–	–	-0.1361*	-0.0708
	–	–	–	–	(0.0812)	(0.0479)
$CUSTC^{\dagger}$	–	–	–	–	-0.0473*	-0.0229
	–	–	–	–	(0.0263)	(0.0145)
Observations	238	248	238	248	238	239
R^2	0.7859	0.5558	0.7860	0.5606	0.7915	0.7543
Wald χ^2	322.25***	132.73***	367.65***	154.79***	420.28***	621.80***

† Segment-level covariates
* significant at 10%, ** at 5%, *** at 1%, standard errors in parenthesis

Table 5: Results for the test of Hypothesis 2.

performance of the automotive segment, as indicated by the positive and statistically significant parameters of *DU* in Table 4. This result contradicts not only Hypothesis 1a, but also most of the literature on market relatedness.

Hypothesis 2

Last, results for the test of Hypothesis 2 are presented in Table 5. Note that the number of observations is reduced because this regression only includes data for the last five years of the sample. Models 4S and 5S are analogous to Models 1S and 2S, respectively, except for the fact that the technological diversification independent variable is introduced.

As predicted, the coefficients for $TECH\_DIV$ have the right negative sign. Model 6S introduces the control variables[14]. Parameters for both performance measures are statistically signif-

[14] Another model contained the *RISK* variable like in Model 3S, but parameters for this covariate were neither signif-

icant and, once again, technological diversification across unrelated fields (3-digit categories in the hierarchical classification[15]) is seen to negatively affect the automotive segment performance. From the parameters in Table 5, it is possible to calculate that the effect of reducing $TECH\_DIV$ by one standard deviation has a positive impact on ROA of approximately 1%, and 0.7% on ROS.

As Table 5 shows, running the regression with only five years had a negative impact on the standard errors of the parameters, reducing the number of those with statistical significance. Another concern is that the coefficients for *DR* in the case of process segments seem to differ in sign (negative here) from those reported in Table 4 (positive). This could indicate that the 1993–1997 sub-sample is intrinsically different from the initial five years of data. To check this, we ran Model 6S without $TECH\_DIV$ for the 5-year and 10-year samples and found the results to agree. There is then no significant difference in the data for the last five years in the sample. Although it is hard to make any inference based on the large standard errors presented in Table 5, it seems logical to conclude that changes in the *DR* coefficients for process segments are a consequence of the introduction of the $TECH\_DIV$ regressor. Furthermore, it is remarkable that the parameter estimation for $TECH\_DIV$ produces such small standard errors (the same being true when the alternate specification $TECH\_COH$ is used), leading us to conclude that there is strong support for Hypothesis 2.

DISCUSSION

At the firm level, our results were weakly supportive of Hypothesis 1a, but not at all of Hypothesis 1b. In general terms, they pointed in the direction of the conclusions of most previous studies about market relatedness, i.e., this has a positive impact on performance, whereas unrelated diversification, on average, hurts the firm. The fact, though, that results are only weakly supportive of this general relatedness hypothesis is not that surprising. A number of previous works have found considerable variance in the performance of both related and unrelated diversifiers (Bettis and Mahajan 1985, Dundas and Richardson 1982, Varadarajan and Ramanujam 1987), meaning that unrelated firms can attain high levels of performance and also that not all related firms do well.

Building upon the framework of product and process firms and how they organize their activities internally, we had particularly hypothesized that a strategy of unrelated diversification could be profitable process-based firms. Nonetheless, we observed that this strategy led to worse performance. In other words, even though process firms are organized along manufacturing operations and seem to be better positioned to act in different industries, our results show that they also can take advantage of operating in closely related industries, i.e., within the same 2-digit SIC code.

icant nor did its presence affect the other estimates. These results are then omitted.

[15] Since we do not operationalize related technological diversification within 3-digit categories, we can also use the Herfindahl index to calculate a conceptually inverse measure of technological diversification ($TECH\_DIV$), i.e., a measure of technological coherence ($TECH\_COH$). Hence, according to Hypothesis 2, we expect its coefficient to be positive. As is well known, for small shares the entropy index is more sensitive than the Herfindahl whereas the opposite is true for little differences in large shares (Jacquemin and Berry 1979). Because we are measuring shares through a simple count of technological capabilities, neither index can claim superiority here. Therefore, for the sake of simplicity and analogy with the market diversification measure, we only report full regression results with $TECH\_DIV$, omitting those with $TECH\_COH$. Nonetheless, the latter coefficients for both ROA and ROS im model 6S were positive, attaining statistical significance at the 1% and 5% level.

This can perhaps be explained as a consequence of the exploitation of strategic assets such as marketing and sales force, or perhaps brand name which might be more industry-specific than expected. That is, in spite of their physical assets being of a generic nature so as to easily serve distinct markets, their marketing and sales competencies might be more specialized than desired or their brands might not carry much value in unrelated markets.

At the segment level, the most puzzling result was the fact that unrelated corporate diversification was beneficial for the automotive product-based segment. There is no simple explanation for this in the literature. However, this particular result and the overall weakness of statistical significance for many market diversification parameters can stem from the problems of inferring relatedness with the use of SIC codes. A major assumption here is the mobility of resources across 4-digit in the same 2-digit SIC code. If this is not the case, it will be much more difficult to identify the benefits of relatedness. In an intra-industry study of personal computers the U.S. for instance, Stern and Henderson (2004) found relatedness benefits only among strikingly similar organizational subunits. To solve these complications, many researchers have called for improved measures of resources at finer levels (Silverman 1999). This would allow one to define a firm's competitive advantage not in terms of end-products but in terms of its strategic assets and capabilities (Teece 1980). In this sense, as Chatterjee and Wernerfelt (1991) have argued, firm performance should be a function not simply of its market diversification strategy, but of the appropriateness of this strategy given its resource endowment.

Measuring capabilities at a much finer level is exactly what we attempted with our hierarchical classification of manufacturing technologies for the automotive business segments. At this finer level, we found strong support for Hypothesis 2, even in the presence of a much reduced sample. This result supports arguments that firms tend to follow patterns of coherent technological diversification around capabilities sharing a common knowledge base (Breschi et al. 2003). If, however, this base is over-extended, the firm will tend to underperform. Results also agree with the survey of the pulp and paper industry presented by Davis, Robinson, Pearce II and Park (1992), who found that profitability was significantly affected by production relatedness (conceptualized as sharing of R&D, plant and equipment), but not marketing relatedness.

We also observed persistent differences between product and process firms and their segments, especially regarding returns to scale and performance. Differences in performance seem to imply that the differentiation strategy followed by product firms is more profitable than the low-cost strategy followed by process firms. Although the lack of scale economies for product firms does not have an economic explanation per se, statistical significant differences in these of economies between product and process firms are in line with our description of their characteristics in the theoretical section.

CONCLUSION AND IMPLICATIONS

This study investigated the roles of market and technological diversification on the financial performance of firms and their business segments operating in the automotive supplier industry. By focusing on a single industry we avoided the inherent problems associated with inter-industry analysis. Starting with the RBV of the firm which argues that the profitable exploitation of excess strategic assets is most likely accomplished via a strategy of related market diversification, this paper attempted to extend this paradigm towards a technological RBV, where the strategic assets are substituted by manufacturing know-how (what a firm makes), and the technical capabilities commanded by the firm take the place of markets. Thus, we predicted that firms that organize their technological capabilities in a coherent way would be able to profit from economies of scope in the use of their specific manufacturing know-how.

Introducing a framework for classifying firms and segments as product- or process-based one, we measured technological diversification at the automotive segment level using a hierarchical classification of product and process capabilities for this industry. We found that, controlling for corporate market diversification, both product and process automotive segments that concentrate their manufacturing capabilities in closely related fields tend to outperform their competitors. This means that valuable manufacturing knowledge which exists within the segment and is also the outcome of learning processes cannot be efficiently transferred to technological areas far afield. Economies of scope in the exploitation of know-how only accrue to closely related production activities in this industry, in an analogous way to the profitable exploitation of strategic assets in closely related markets, in the RBV paradigm.

This research has a number of implications for the management of companies and innovation. For example, managers should pay more attention to the technological coherence of their firms and the knowledge base underlying their manufacturing competencies. When planning diversification moves, they should make sure that they have the required technical capabilities in addition to considering the use of their more traditional assets and the necessity of acquiring complementary ones. Results suggest that concentrating the technological capabilities of the segment in coherent areas may be an easier path to increasing performance than relying on economies of scope with other segments achieved through firm-level related market diversification.

Furthermore, managers should bear in mind the distinction between knowledge embedded in patents and that present in manufacturing operations, especially the importance of the tacit component in the latter. While it might be fruitful to proceed with exploratory research in technological areas far afield, as suggested by Gambardella and Torrisi (1998), this does not necessarily mean that the firm should start producing in these new fields right away, even if market opportunities exist. When patents are a strong instrument of intellectual protection, successful exploratory R&D coupled with lack of manufacturing know-how should prompt firms to seek licensing or alternative productive collaborative agreements with other organizations.

Finally, results presented here have important ramifications into management of innovation. Breschi et al. (2003) have argued that firms should pursue a coherent portfolio of innovative activities by commanding different technologies that share an underlying related knowledge base. With the caveat that this is probably more true of exploitative innovations in mature industries such as the automotive, perhaps Nelson (1991) has put it better when stating that “firms need to learn to get good at certain kinds of innovation and this requires concentration or at least coherency, rather than random spreading of efforts.” And to the extent that R&D tends to be financed with internal funds, the present study indirectly implies that because the concentration of capabilities leads to higher returns, coherent firms might also be in a better position to innovate.

ACKNOWLEDGEMENTS

We thank participants in the Strategy, Entrepreneurship and Technological Change seminar at Carnegie Mellon, especially Peter Thompson and Rob Lowe, for valuable input. This paper also benefited from comments received from Rosemarie Ziedonis and three anonymous reviewers at the Academy of Management 2004 annual meeting, as well as during an earlier draft presentation at the Production and Operations Management Society 2003 annual meeting. Financial support was provided by the International Motor Vehicle Program at the Massachusetts Institute of Technology, Fundação Ciência e Tecnologia (FCT), Portugal, through project grant 42087/GES/2001, and a doctoral fellowship from Fundação Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES), Brazil.

REFERENCES

Argote, L. and D. Epple, "Learning curves in manufacturing," *Science*, 1990, *247*, 920–924.

Beck, N. and J.N. Katz, "What to do (and not to do) with time-series cross-sectional data," *American Political Science Review*, 1995, *89* (3), 634–647.

____ **and** ____ , "Nuisance vs. substance: specifying and estimating time-series-cross-section models," *Political Analysis*, 1996, *6*, 1–36.

Bettis, R.A., "Performance differences in related and unrelated diversified firms," *Strategic Management Journal*, 1981, *2* (4), 379–393.

____ **and V. Mahajan**, "Risk/return performance of diversified firms," *Management Science*, 1985, *31* (7), 785–799.

Breschi, S., F. Lissoni, and F. Malerba, "Knowledge-relatedness in firm technological diversification," *Research Policy*, 2003, *32*, 69–87.

Brusoni, S., A. Prencipe, and K. Pavitt, "Knowledge specialization, organizational coupling, and the boundaries of the firm: why do firms know more than they make?," *Administrative Science Quarterly*, 2001, *46*, 597–621.

Chandler, A.D., *Strategy and structure: chapters in the history of the industrial enterprise*, MIT Press, 1962.

Chatterjee, S. and B. Wernerfelt, "The link between resources and type of diversification: theory and evidence," *Strategic Management Journal*, 1991, *12* (1), 33–48.

Christensen, H.K. and C.A. Montgomery, "Corporate economic performance: diversification strategy versus market structure," *Strategic Management Journal*, 1981, *2* (4), 327–343.

Clark, K.B. and T. Fujimoto, *Product development performance: strategy, organization, and management in the world auto industry*, Harvard Business School Press, 1991.

Coase, R.H., "The nature of the firm," *Economica*, 1937, *4* (16), 386–405.

Davis, P.S., R.B. Robinson, J.A. Pearce II, and S.H. Park, "Business unit relatedness and performance: a look at the pulp and paper industry," *Strategic Management Journal*, 1992, *13* (5), 349–361.

Dierickx, I. and K. Cool, "Asset stock accumulation and sustainability of competitive advantage," *Management Science*, 1989, *35* (12), 1504–1511.

Dundas, K.N.M. and P.R. Richardson, "Implementing the unrelated product strategy," *Strategic Management Journal*, 1982, *3* (4), 287–301.

Eisenhardt, K.M. and J.A. Martin, "Dynamic capabilities: what are they?," *Strategic Management Journal*, 2000, *21* (10-11), 1105–1121.

Fisher, F.M. and J.J. McGowan, "On the misuse of accounting rates of return to infer monopoly profits," *The American Economic Review*, 1983, *73* (1), 82–97.

Gambardella, A. and S. Torrisi, "Does technological convergence imply convergence in markets? Evidence from the electronics industry," *Research Policy*, 1998, *27*, 445–463.

Gort, M., *Diversification and integration in American industry*, Princeton University Press, 1962.

Hammer, M. and S. Stanton, "How process enterprises really work," *Harvard Business Review*, 1999, *77* (6), 108–118.

Hawawini, G., V. Subramanian, and P. Verdin, "Is performance driven by industry- or firm-specific factors? A new look at the evidence," *Strategic Management Journal*, 2003, *24* (1), 1–16.

Hayes, R.M. and S.C. Wheelwright, "The dynamics of process-product life cycles," *Harvard Business Review*, 1979, *57* (2), 127–136.

____ , ____ , and K.B. Clark, *Dynamic manufacturing: creating the learning organization*, Free Press, 1988.

Helfat, C.E., "Guest editor's introduction to the special issue: the evolution of firm capabilities," *Strategic Management Journal*, 2000, *21* (10-11), 955–959.

Jacquemin, A.P. and C.H. Berry, "Entropy measure of diversification and corporate growth," *The Journal of Industrial Economics*, 1979, *27* (4), 359–369.

Kodama, F., "Technological diversification of Japanese industry," *Science*, 1986, *233* (4761), 291–296.

Lindenberg, E.B. and S.A. Ross, "Tobin's *q* ratio and industrial organization," *Journal of Business*, 1981, *54* (1), 1–32.

Lowe, R.A., "Personal knowledge, information asymmetry, and university entrepreneurship," 2003. Working paper, Carnegie Mellon University.

MacDuffie, J.P., K. Sethuraman, and M.L. Fisher, "Product variety and manufacturing performance: evidence from the International Automotive Assembly Plant Study," *Management Science*, 1996, *42* (3), 350–369.

Malerba, F., “Sectoral systems of innovation and production,” *Research Policy*, 2002, *31*, 247–264.

Monteverde, K. and D.J. Teece, “Supplier switching costs and vertical integration in the automobile industry,” *The Bell Journal of Economics*, 1982, *13* (1), 206–213.

Montgomery, C.A., “The measurement of firm diversification: some new empirical evidence,” *Academy of Management Journal*, 1982, *25* (2), 299–307.

—— **and B. Wernerfelt**, “Diversification, Ricardian rents, and Tobin’s *q*,” *The RAND Journal of Economics*, 1988, *19* (4), 623–632.

Mowery, D.C. and R.R. Nelson, “Explaining industrial leadership,” in D.C. Mowery and R.R. Nelson, eds., *Sources of Industrial Leadership*, Cambridge University Press, 1999, chapter 9, pp. 359–382.

Nelson, R.R., “Why do firms differ, and how does it matter?,” *Strategic Management Journal*, 1991, *12* (Special Issue: Fundamental Research Issues in Strategy and Economics), 61–74.

Palepu, K., “Diversification strategy, profit performance and the entropy measure,” *Strategic Management Journal*, 1985, *6* (3), 239–255.

Palich, L.E., L.B. Cardinal, and C.C. Miller, “Curvilinearity in the diversification-performance linkage: an examination of over three decades of research,” *Strategic Management Journal*, 2000, *21* (2), 155–174.

Panzar, J.C. and R.D. Willig, “Economies of scope,” *The American Economic Review*, 1981, *71* (2), 268–272.

Pavitt, K., M. Robson, and J. Townsend, “Technological accumulation, diversification and organisation in UK companies, 1945–1983,” *Management Science*, 1989, *35* (1), 81–99.

Penrose, E.T., *The theory of the growth of the firm*, Basil Blackwell Publisher, 1959.

Peteraf, M.A., “The cornerstones of competitive advantage: a resource-based view,” *Strategic Management Journal*, 1993, *14* (3), 179–191.

Pisano, G.P., *The development factory: unlocking the potential of process innovation*, Harvard Business School Press, 1997.

Porter, M.E., *Competitive strategy: techniques for analyzing industries and competitors*, Simon & Schuster Adult Publishing Group, 1980.

—— , “From competitive advantage to corporate strategy,” *Harvard Business Review*, 1987, *65* (3), 43–59.

Ramanujam, V. and P. Varadarajan, “Research on corporate diversification: a synthesis,” *Strategic Management Journal*, 1989, *10* (6), 523–551.

Rotemberg, J.J. and G. Saloner, “Benefits of narrow business strategies,” *The American Economic Review*, 1994, *84* (5), 1330–1349.

Rubin, P.H., “The expansion of firms,” *Journal of Political Economy*, 1973, *81* (4), 936–949.

Rumelt, R.P., “Diversification strategy and profitability,” *Strategic Management Journal*, 1982, *3* (4), 359–369.

Schroeder, R.G., K.A. Bates, and M.A. Juntilla, “A resource-based view of manufacturing strategy and the relationship to manufacturing performance,” *Strategic Management Journal*, 2002, *23* (2), 105–117.

Silverman, B.S., “Technological resources and the direction of corporate diversification: toward an integration of the resource-based view and the transaction cost economics,” *Management Science*, 1999, *45* (8), 1109–1124.

St. John, C.H. and J.S. Harrison, “Manufacturing-based relatedness, synergy, and coordination,” *Strategic Management Journal*, 1999, *20* (2), 129–145.

Steinemann, P.P., “Economic performance of product and process firms: focus and diversification in the automotive supplier industry.” PhD dissertation, Massachusetts Institute of Technology 2000.

Stern, I. and A.D. Henderson, “Within-business diversification in technology-intensive industries,” *Strategic Management Journal*, 2004, *25*, 487–505.

Takeishi, A., “Knowledge partitioning in the interfirm division of labor: the case of automotive product development,” *Organization Science*, 2002, *13* (3), 321–338.

Teece, D.J., “Technology transfer by multinational firms: the resource cost of transferring technological know-how,” *The Economic Journal*, 1977, *87* (346), 242–261.

____ , “Economies of scope and the scope of the enterprise,” *Journal of Economic Behavior and Organization*, 1980, *1*, 223–247.

____ , “Towards an economic theory of the multiproduct firm,” *Journal of Economic Behavior and Organization*, 1982, *3*, 39–63.

Varadarajan, P.R. and V. Ramanujam, “Diversification and performance: a reexamination using a new two-dimensional conceptualization of diversity in firms,” *Academy of Management Journal*, 1987, *30* (2), 380–393.

Wernerfelt, B., “A resource-based view of the firm,” *Strategic Management Journal*, 1984, *5* (2), 171–180.

Wooldridge, J.M., *Econometric analysis of cross section and panel data*, MIT Press, 2001.

APPENDIX A – CRITERIA FOR CLASSIFYING TECHNOLOGICAL CAPABILITIES

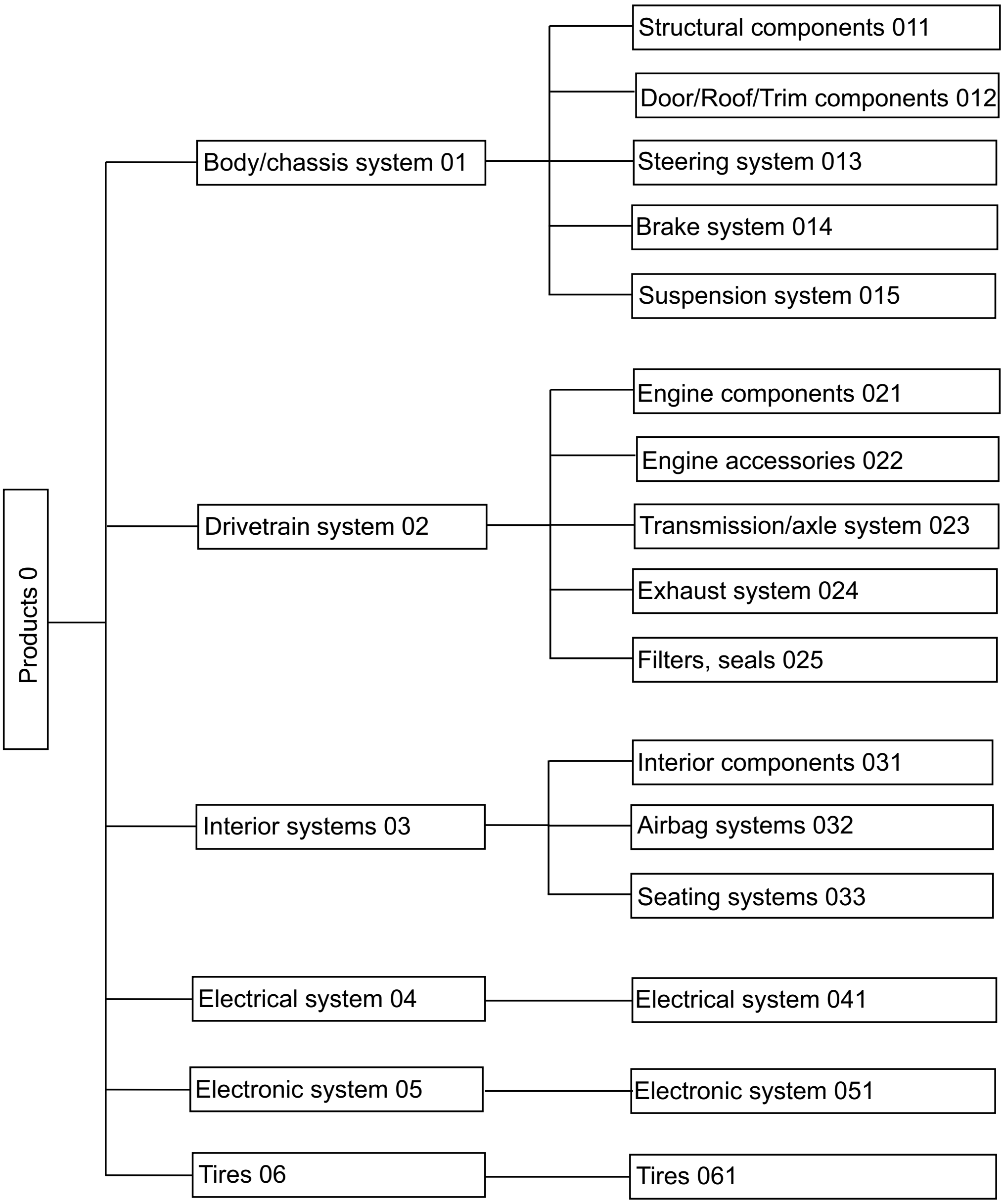
The interrelationship of products was based on:

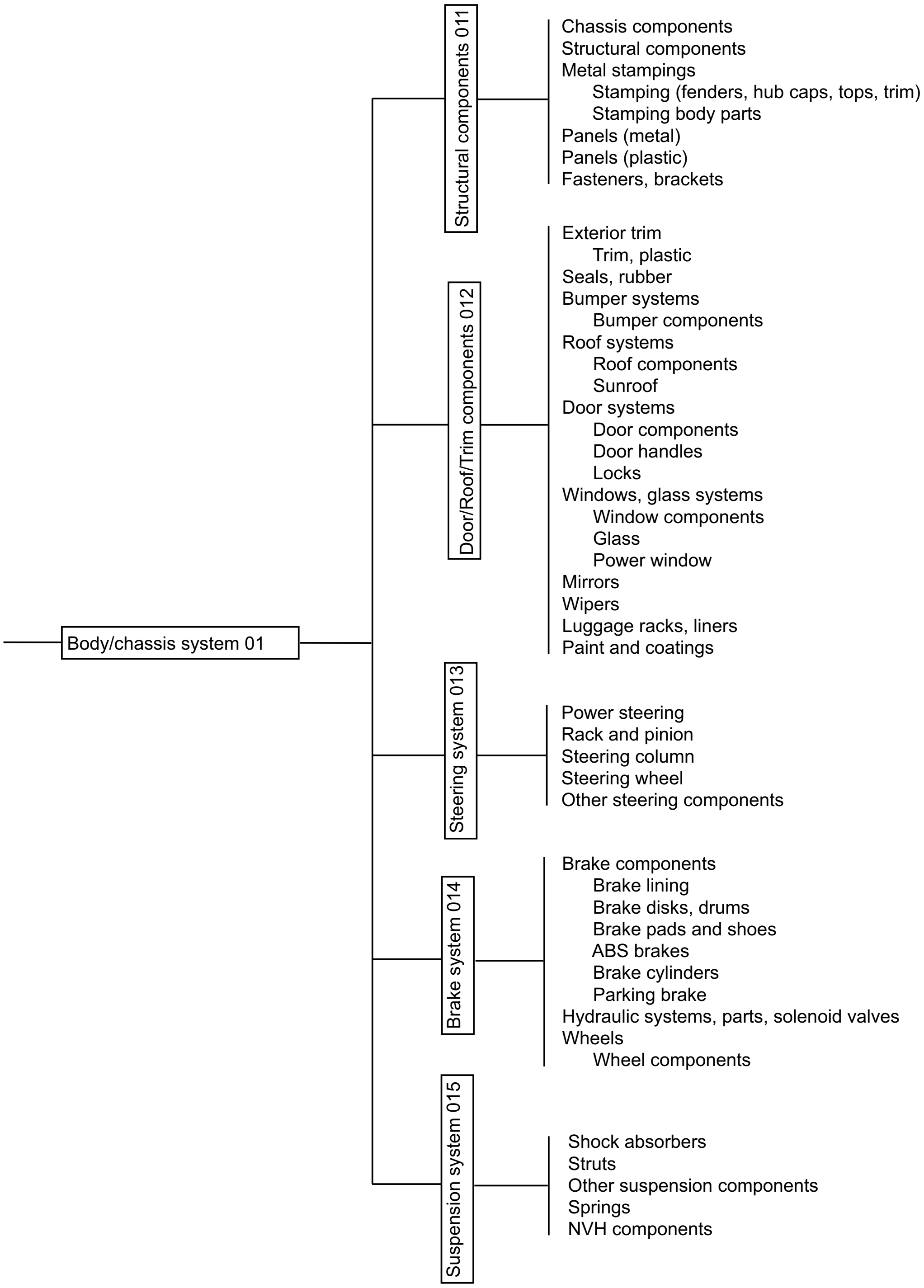
- Similarities in science and technology
  - Scientific and technical knowledge requirement
  - Intellectual property basis
- Similarities in engineering, design and marketing
  - Development requirements
    - Lead time
    - Coordination
    - Prototyping and testing
  - Product economics
    - Development and engineering costs
    - Manufacturing and assembly requirements (costs and production volume)
    - Logistics requirements
  - Marketing requirements
- Similarities in functionality and price
  - Functional requirements (performance, features, reliability, durability)
  - Complexity
  - Price requirements

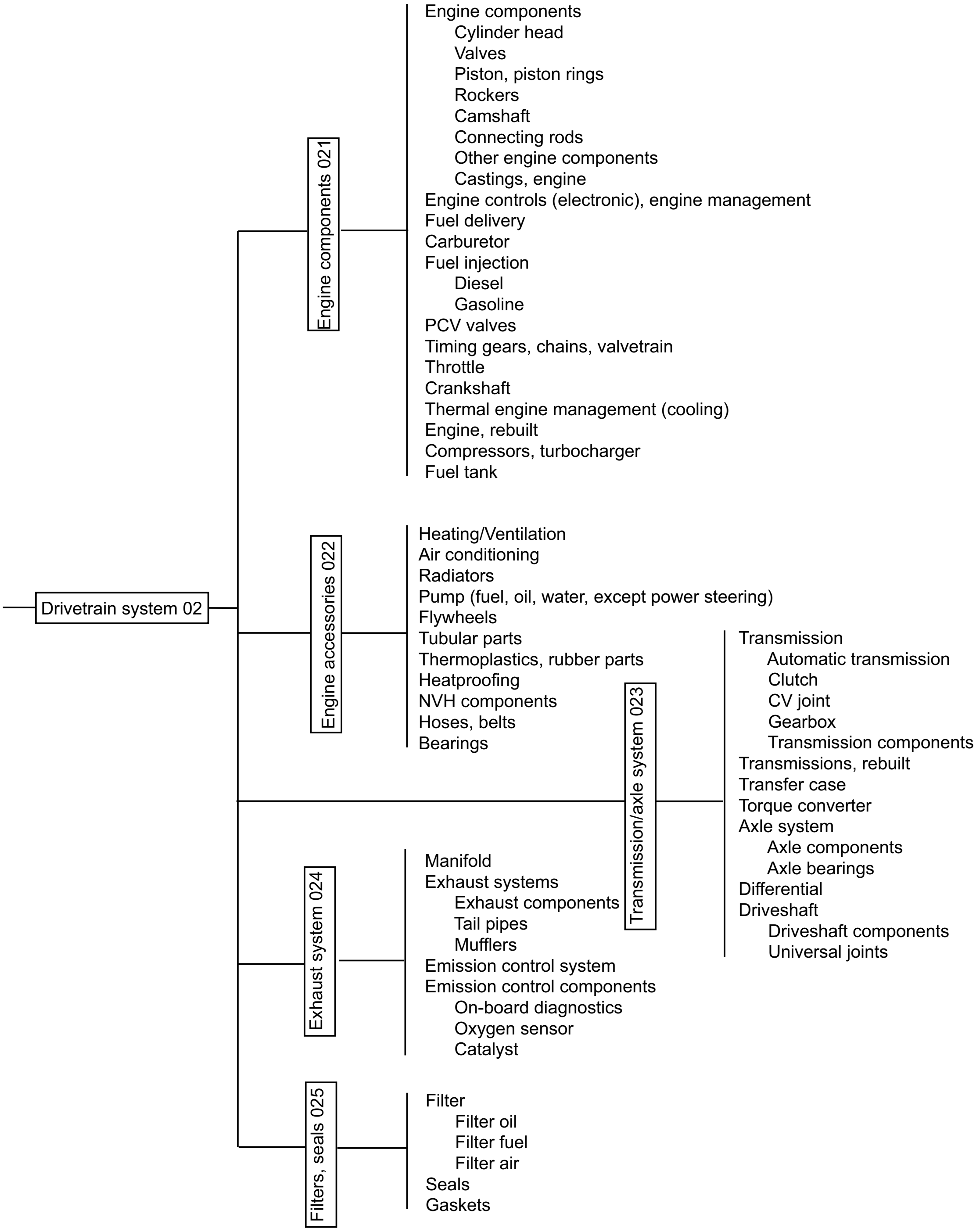
Analogously, technological interrelationships between processes were based on:

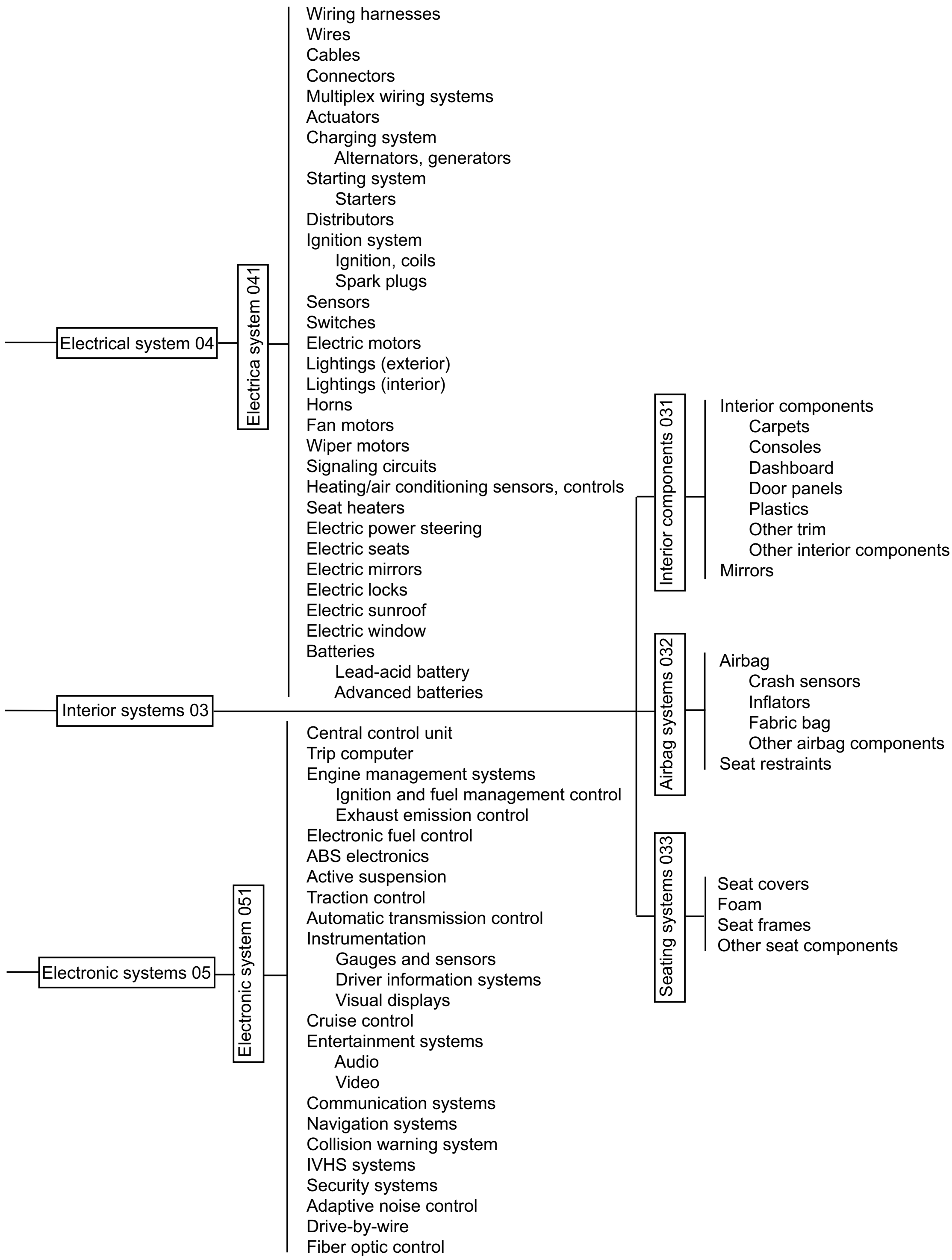
- Similarities in properties of processed materials
  - Manufacturing properties, mechanical behavior (tension, compression, torsion, bending, hardness, fatigue, creep, impact)
  - Physical properties (density, melting point, thermal conductivity, corrosion)
- Similarities in manufacturing process
  - Process conditions (work, heat, temperature, moisture)
  - Process methods
    - Equipment requirements
    - Coordination requirements
  - Quality, testing and inspection requirements
  - Process economics
    - Materials costs
    - Equipment costs
    - Operating costs (operation, tooling, service and maintenance)
    - Production volume and rate

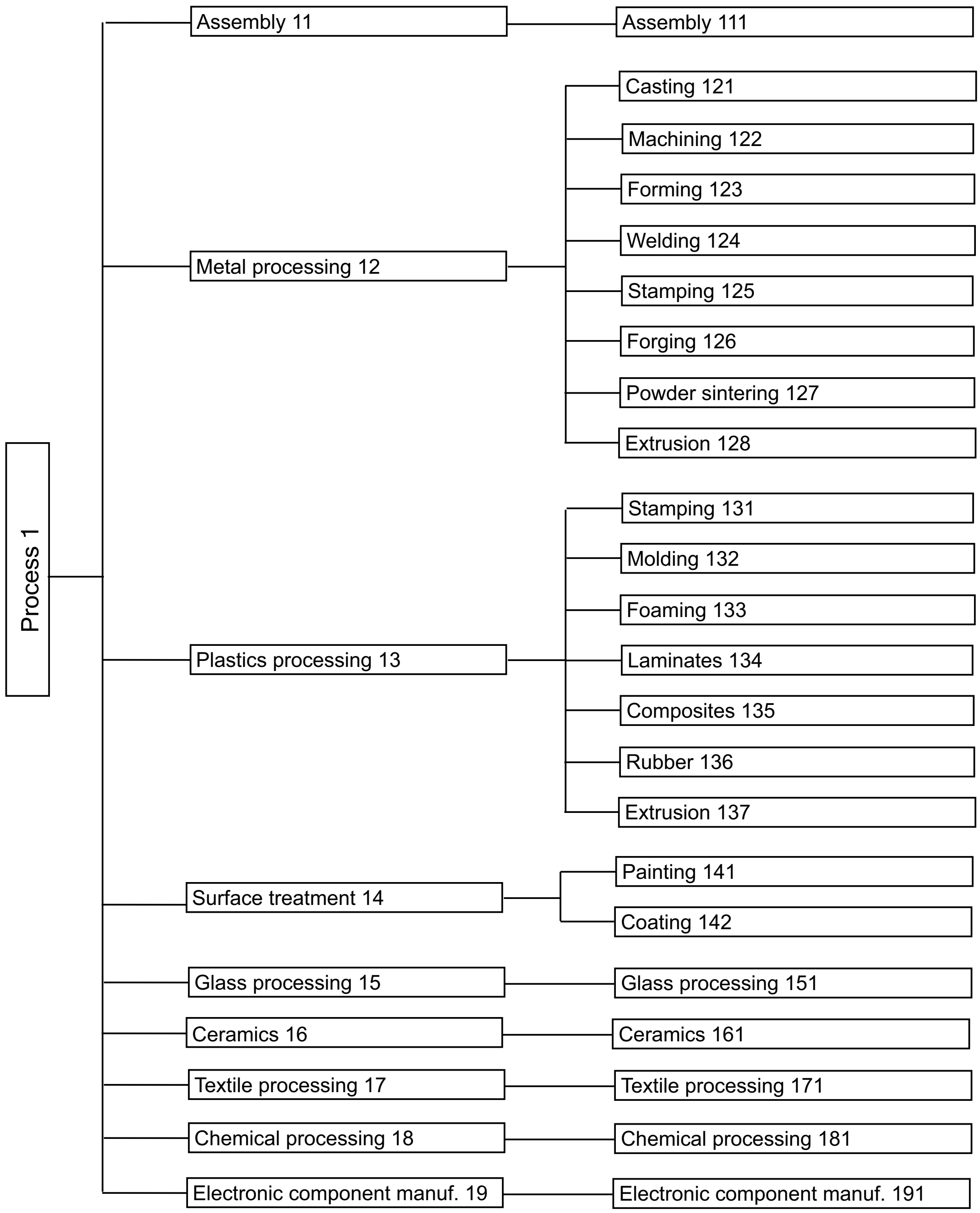
APPENDIX B – PRODUCT AND PROCESS HIERARCHICAL CLASSIFICATION SCHEME

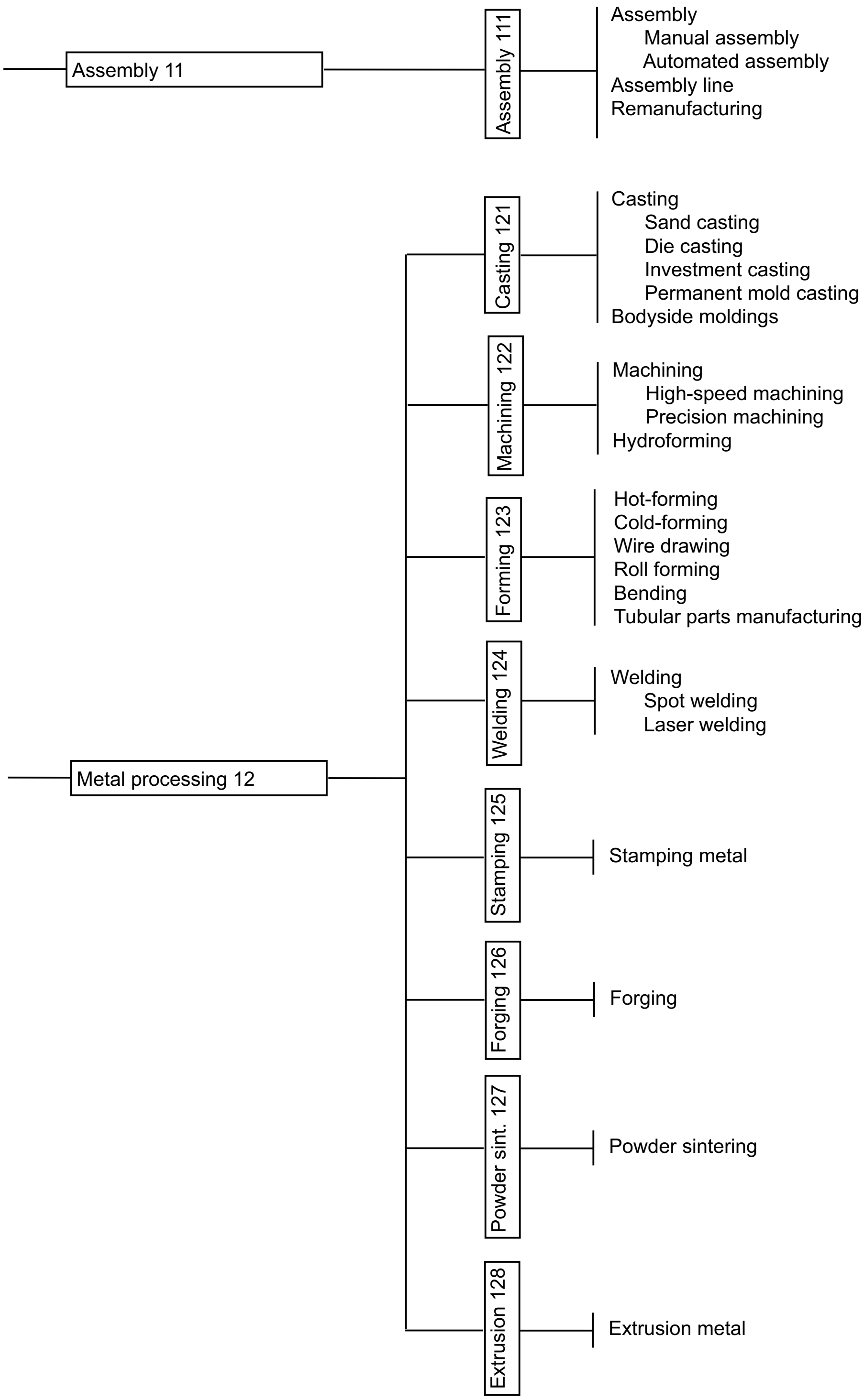


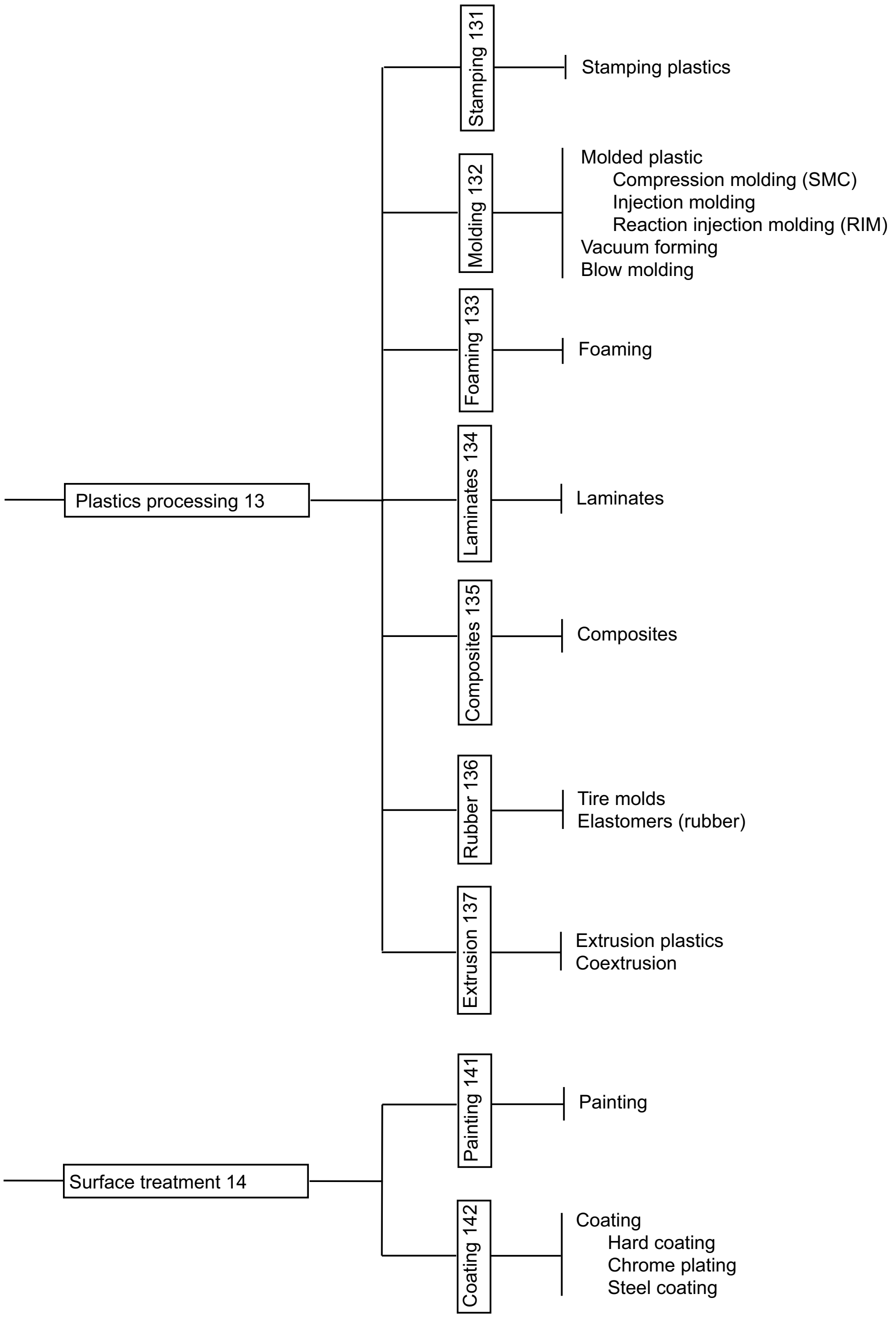

Body/chassis system 01
Structural components 011
Chassis components
Structural components
Metal stampings
Stamping (fenders, hub caps, tops, trim)
Stamping body parts
Panels (metal)
Panels (plastic)
Fasteners, brackets
Door/Roof/Trim components 012
Exterior trim
Trim, plastic
Seals, rubber
Bumper systems
Bumper components
Roof systems
Roof components
Sunroof
Door systems
Door components
Door handles
Locks
Windows, glass systems
Window components
Glass
Power window
Mirrors
Wipers
Luggage racks, liners
Paint and coatings
Steering system 013
Power steering
Rack and pinion
Steering column
Steering wheel
Other steering components
Brake system 014
Brake components
Brake lining
Brake disks, drums
Brake pads and shoes
ABS brakes
Brake cylinders
Parking brake
Hydraulic systems, parts, solenoid valves
Wheels
Wheel components
Suspension system 015
Shock absorbers
Struts
Other suspension components
Springs
NVH components


Drivetrain system 02
Engine components 021
Engine components
Cylinder head
Valves
Piston, piston rings
Rockers
Camshaft
Connecting rods
Other engine components
Castings, engine
Engine controls (electronic), engine management
Fuel delivery
Carburetor
Fuel injection
Diesel
Gasoline
PCV valves
Timing gears, chains, valvetrain
Throttle
Crankshaft
Thermal engine management (cooling)
Engine, rebuilt
Compressors, turbocharger
Fuel tank
Engine accessories 022
Heating/Ventilation
Air conditioning
Radiators
Pump (fuel, oil, water, except power steering)
Flywheels
Tubular parts
Thermoplastics, rubber parts
Heatproofing
NVH components
Hoses, belts
Bearings
Transmission/axle system 023
Transmission
Automatic transmission
Clutch
CV joint
Gearbox
Transmission components
Transmissions, rebuilt
Transfer case
Torque converter
Axle system
Axle components
Axle bearings
Differential
Driveshaft
Driveshaft components
Universal joints
Exhaust system 024
Manifold
Exhaust systems
Exhaust components
Tail pipes
Mufflers
Emission control system
Emission control components
On-board diagnostics
Oxygen sensor
Catalyst
Filters, seals 025
Filter
Filter oil
Filter fuel
Filter air
Seals
Gaskets


Electrical system 04
Electrica system 041
Wiring harnesses
Wires
Cables
Connectors
Multiplex wiring systems
Actuators
Charging system
Alternators, generators
Starting system
Starters
Distributors
Ignition system
Ignition, coils
Spark plugs
Sensors
Switches
Electric motors
Lightings (exterior)
Lightings (interior)
Horns
Fan motors
Wiper motors
Signaling circuits
Heating/air conditioning sensors, controls
Seat heaters
Electric power steering
Electric seats
Electric mirrors
Electric locks
Electric sunroof
Electric window
Batteries
Lead-acid battery
Advanced batteries
Interior systems 03
Interior components 031
Interior components
Carpets
Consoles
Dashboard
Door panels
Plastics
Other trim
Other interior components
Mirrors
Airbag systems 032
Airbag
Crash sensors
Inflators
Fabric bag
Other airbag components
Seat restraints
Seating systems 033
Seat covers
Foam
Seat frames
Other seat components
Electronic systems 05
Electronic system 051
Central control unit
Trip computer
Engine management systems
Ignition and fuel management control
Exhaust emission control
Electronic fuel control
ABS electronics
Active suspension
Traction control
Automatic transmission control
Instrumentation
Gauges and sensors
Driver information systems
Visual displays
Cruise control
Entertainment systems
Audio
Video
Communication systems
Navigation systems
Collision warning system
IVHS systems
Security systems
Adaptive noise control
Drive-by-wire
Fiber optic control


Process 1
Assembly 11
Assembly 111
Metal processing 12
Casting 121
Machining 122
Forming 123
Welding 124
Stamping 125
Forging 126
Powder sintering 127
Extrusion 128
Plastics processing 13
Stamping 131
Molding 132
Foaming 133
Laminates 134
Composites 135
Rubber 136
Extrusion 137
Surface treatment 14
Painting 141
Coating 142
Glass processing 15
Glass processing 151
Ceramics 16
Ceramics 161
Textile processing 17
Textile processing 171
Chemical processing 18
Chemical processing 181
Electronic component manuf. 19
Electronic component manuf. 191


Assembly 11
Assembly 111
Assembly
Manual assembly
Automated assembly
Assembly line
Remanufacturing
Metal processing 12
Casting 121
Casting
Sand casting
Die casting
Investment casting
Permanent mold casting
Bodyside moldings
Machining 122
Machining
High-speed machining
Precision machining
Hydroforming
Forming 123
Hot-forming
Cold-forming
Wire drawing
Roll forming
Bending
Tubular parts manufacturing
Welding 124
Welding
Spot welding
Laser welding
Stamping 125
Stamping metal
Forging 126
Forging
Powder sint. 127
Powder sintering
Extrusion 128
Extrusion metal


Plastics processing 13
Stamping 131
Stamping plastics
Molding 132
Molded plastic
Compression molding (SMC)
Injection molding
Reaction injection molding (RIM)
Vacuum forming
Blow molding
Foaming 133
Foaming
Laminates 134
Laminates
Composites 135
Composites
Rubber 136
Tire molds
Elastomers (rubber)
Extrusion 137
Extrusion plastics
Coextrusion
Surface treatment 14
Painting 141
Painting
Coating 142
Coating
Hard coating
Chrome plating
Steel coating