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Abstract

Uncertainty has long been understood as a stimulus for firms to manage their boundaries, i.e., to define the scope of their activities. However, two to some extent competing strategy perspectives – governance and competence – predict that firms faced with uncertainty would either increase or decrease their scope of activities, respectively. In an attempt to reconcile these conflicting positions, we propose a model in which the system-level property *knowledge interdependence* moderates the effect of technological uncertainty on firms' R&D scope decisions. To test our model empirically, we develop a new set of measures for knowledge interdependence and technological uncertainty, and collect 33 years of data (1967-2000) on patenting activity and firm boundary location in the automotive airbag industry. The results of our analysis generally support our model, and show that in case of knowledge-creating activities such as R&D, scope decisions under technological uncertainty are more driven by concerns about co-specialization effects than transaction efficiencies. We discuss implications of these findings for managerial practice and future research.

Keywords

Knowledge interdependence, Modularity, Technological Uncertainty, Research and Development, Firm boundary, Complex Technological Products, Industry Emergence

1 INTRODUCTION

The scholarly investigation of how firms respond to uncertainty in their environment stretches back for at least half a century (March and Simon, 1958; Thompson, 1967). One aspect of major interest in this literature stream on the effects of uncertainty on firm behavior is the decision on where to locate the firm boundary, i.e., the decision on which activities to maintain inside the firm and which activities to access outside of the firm through market mechanisms. While the majority of this work has focused in the past on the world of production, the recently growing relevance of knowledge work has raised this question also in the arena of knowledge-creating activities such as research and development (R&D).

The transfer of the existing arguments from production to R&D has led to some conflicting explanations from two separate viewpoints, following Williamson (1999) here labeled as governance and competence perspectives. One argument suggests that the appropriate response to an increase in technological uncertainty is to enlarge the firm's boundary to integrate more activities in-house to reduce the risk of opportunism (Hoetker, 2005; Pisano, 1990; Williamson, 1985). However, another argument suggests the opposite, i.e., that firms facing high levels of technological uncertainty decrease the range of their internal R&D activities to avoid the risk of obsolescence (Balakrishnan and Wernerfelt, 1986; Levinthal and March, 1981; Santoro and McGill, 2005).

To reconcile these conflicting arguments we strive to explain these variations through the underlying – often only implicit – assumptions on the structure of the relevant knowledge involved. More specifically, building on modularity theory we develop a model in which the property *knowledge interdependence* moderates the effect of exogenous technological uncertainty on firms' R&D scope decisions, and thus the range of their knowledge development work. The model suggests that in regimes of high knowledge interdependence the co-specialization effects outweigh transaction efficiency considerations. Conversely, in low knowledge interdependence regimes the model predicts that transaction considerations dominate co-specialization effects. We empirically test our model with longitudinal data of 33 years (1967–2000) on patenting activity and firm boundary location from the automotive airbag industry and find support for the model, albeit with some modification.

The paper is organized as follows. In the next section we lay out the theoretical background, propose our model, and develop hypotheses. In section three we introduce the data and develop new measures. The empirical results follow in section four, and section five discusses theoretical and managerial implications of the results.

2 BACKGROUND AND HYPOTHESES

2.1 Effects of Technological Uncertainty on R&D Scope

Various scholars have identified uncertainty as an important factor explaining firms' decisions on R&D scope. Uncertainty has been identified as a key variable affecting organizational behavior (March and Simon, 1958), and coping with this uncertainty becomes a primary task for firms (Thompson, 1967). Uncertainty has also been described as one of several critical dimensions deciding the costs of transactions (Williamson, 1981). Note that among different types of uncertainty (e.g., demand uncertainty, customer preference uncertainty, supply uncertainty, fuzziness, etc.) (Sicotte and Bourgault, 2008), our focus here is on technological uncertainty as it is particularly relevant in technology-intensive industries for decisions on R&D scope. Moreover, we consider technological uncertainty as a type of primary uncertainty (Helfat and Teece, 1987) which reflects the uncertainty arising from exogenous sources such as natural events, regulatory changes, or industry-level technological changes. Therefore, technological uncertainty influences an industry as a whole and cannot be controlled by any one firm (Helfat and Teece, 1987; Sutcliffe and Zaheer, 1998).

While there is agreement that uncertainty matters in determining effective R&D firm boundary locations, different conclusions seem to be drawn as to *how* it matters. One stream of studies, the governance perspective building on the transaction cost economics (TCE) tradition, focuses on the efficiency of transactions in explaining firms' decisions on their R&D scope. Uncertainty raises the risk of opportunism in market relationships, thus raises their costs, and makes the fact that separate companies do not 'speak the same dialect' more problematic (Poppo and Zenger, 1998; Williamson, 1981). Uncertainty also increases the risk of failure of a technological development, and in the event of failure, it is often difficult to determine who is at fault among contracting parties (Hoetker, 2005). Seen from the TCE perspective, therefore, firms expand their R&D scope as uncertainty increases to lower the risk of being exposed to opportunism.

Another stream of studies views the problem from a different angle. The resource-based view (RBV), later expanded into knowledge and, more generally, capabilities, and here labeled as the competence perspective, focuses on the rare, valuable, and inimitable aspect of firms that lead to interfirm performance variation.[1] Some studies in the RBV tradition have emphasized the benefits of co-specialization (Makadok, 2001; Teece, 1982). To obtain the benefits of co-specialization, firms are often required to broaden their R&D scope to acquire new knowledge (Kogut and Zander, 1992; Leonard-Barton, 1992; Teece, Pisano and Shuen, 1997) or to understand related knowledge better (Brusoni, Prencipe and Pavitt, 2001; Granstrand, Patel and Pavitt, 1997). On the other hand, high levels of uncertainty increase the risk of obsolescence of the system and thus can significantly reduce the benefits of integration (Balakrishnan and Wernerfelt, 1986; Santoro and McGill, 2005). Moreover, firms can build specialized expertise by focusing on familiar knowledge (Prahalad and Hamel, 1990) and familiar knowledge tends to yield more reliable results (Levinthal and March, 1981; Nelson and Winter, 1982). Seen from this competence perspective, firms tend to reduce their R&D scope when uncertainty increases.

More recently, researchers have proposed to develop views and approaches that combine the two perspectives above, often by incorporating additional elements such as context, interaction, and innovation. For example, Madhok (2002) calls for triangular alignment of transaction attributes, resource attributes and governance skills, and suggests that "both TC[E] and RB[V] theory need to pay more attention to the context within which the activity occurs" (Madhok, 2002:542). Similarly, Jacobides and Winter (2005) argue that TCE and RBV are in reality intertwined as their drivers interact with each other while they co-evolve. In their view, not only do transaction costs moderate the effect of the capability distribution on vertical scope, the scope itself affects the capability development process which determines the capability distribution, which in turn also motivates a change of the transaction costs. Finally, Wolter and Veloso (2008) explore the question of vertical structure as response to an exogenous shock (i.e., technological innovation) to the industry. Building on Henderson and Clark's (1990) typology of incremental, modular, architectural, and radical innovations Wolter and Veloso propose that the degree of vertical integration in an industry will not change in response to an incremental innovation, will decrease in response to a modular innovation, and will increase in response to architectural and radical innovations.

Extending this stream of recent research we turn our attention to another contextual variable: the structure that characterizes the knowledge created during the invention process. We propose that the degree to which knowledge components are interdependent helps explain whether TCE or RBV has greater explanatory power in predicting R&D scope.

2.2 Interdependence

One of the criticisms of TCE has been that with the individual transaction as its unit of analysis it has assumed overly simplified systems. As Williamson himself states "[t]he practice of examining transactions 'as if' they were independent will not do if there are significant interaction effects between them" (Williamson, 1999:1102). The RBV perspective, with its focus on differences between firms, suggests that firm A's difficulty to copy firm B's practices is due to the opaqueness of B's practices to begin with. One aspect that underlies this difficulty to understand another firm's set of routines, practices, and skills is their interconnectedness (Lenox, Rockart and Lewin, 2010).

A powerful way to think about this aspect of interconnectedness is to apply modularity theory. Almost half a Century ago Simon (1962) introduced the concept of near-decomposability as a solution to limit system complexity and avoid cognitive overload. Later, researchers added the insight of the critical role of task division (von Hippel, 1990), of how organizational structures come to mirror the structure of the products these organizations produce (Henderson and Clark, 1990), and of how product structures and industry structures are related (Langlois and Robertson, 1992). Following this work, Schilling (2000) proposes a model that products and systems strive to find a degree of modularity that balances external forces, and Baldwin and Clark (2000) develop a theory of operators that explains how systems evolve to become more modular. Over the past fifteen years, the concept of modularity has been applied in various contexts such as product and process development (Fixson, 2007) and has been further investigated and interpreted as a composite construct (Salvador, 2007).

On the product level, Ulrich (1995) laid the foundation for our understanding of modularity as a key aspect of product architecture. Since then, product architectures and their multiple dimensions have been linked to various firm effects and industry outcomes, ranging from operational performance measures in processes and supply chains (Fixson, 2005), to the appropriate relationship between buyers and suppliers (Hsuan Mikkola, 2003). Baldwin (2008) clarifies the mechanisms through which modularity affects the underlying task and transfer network, and subsequently the location of firm boundaries.

Modularity has also been invoked on the knowledge level. Admittedly, more abstract than the product level, knowledge has been identified as having various attributes, for example, tacit vs. explicit (Nonaka, 1991), competence-enhancing vs. competence-destroying (Tushman and Anderson, 1986), firm-specific vs. non firm-specific (Chen and Lin, 2004), or easy to recombine vs. not so easy to recombine (Fleming and Sorenson, 2001). It is this fourth characterization of knowledge, the degree to which it is 'recombinable,' that borrows from modularity theory to define interdependence, albeit introducing a subtle distinction: "[i]nterdependence is the intrinsic or potential interaction between components, while modularity is the consciously designed de-coupling of components" (Fleming and Sorenson, 2001:1036).

We propose that such a construct of interdependence between knowledge components – modeled as the inverse of the loose coupling idea of modularity – can help explain why TCE and RBV produce different predictions for a firm's R&D scope response when facing technological uncertainty. Note that we describe knowledge interdependence as a phenomenon that exists on the industry level and is dynamic. While it is possible that the interdependence between components of a *product* varies from design to design, i.e., multiple designs can exist in an industry, we focus our attention on the interdependence of the components of the underlying *knowledge* structure. This knowledge structure is an industry-level characteristic, and not necessarily related to the product structure (Brusoni and Prencipe, 2001). It is also not static but can change over time with technology changes as the aggregate outcome of the search activities of firms (Nelson and Winter, 1982).

2.3 Hypotheses

Fundamentally, the TCE perspective assumes one unit of analysis, a transaction, as more or less independent of the next transaction. In other words, TCE implicitly assumes a very low level of interdependence between the 'components' under consideration. In contrast, the RBV perspective focuses on resources that are difficult to imitate by competitors. One aspect that makes a set of 'components' difficult to imitate is their level of interconnectedness, i.e., the complex system they form via their interdependencies. In short, the two perspectives appear to build on different assumptions concerning the underlying knowledge structure. We use this difference in assumptions to formulate our first hypothesis.

Hypothesis 1: Interdependence of knowledge components changes the relationship between R&D scope and technological uncertainty.

In addition, we hypothesize *how* different degrees of knowledge component interdependence affect the relationship between technological uncertainty and R&D scope. To do so we compare the factors which reduce or increase R&D scope, once for a high interdependence regime, and once for a low interdependence regime. Table 1 summarizes the hypothesized relationships.

The TCE perspective's key concern is the reduction of opportunistic behavior and its associated costs. Technological uncertainty increases the risk of opportunism, thus TCE would recommend to increase R&D scope with increasing uncertainty. However, in high interdependence regimes, the interconnectedness of components already keeps the possibilities for behaving opportunistically in check. Consequently, integration via increasing R&D scope offers little *additional* insurance against opportunism.

The RBV perspective suggests that there are substantial benefits achievable by creating a system of interdependent components. Because tightly coupled components require developers to communicate frequently and openly, forms of intrafirm collaboration appear to be advantageous. At the same time, there are risks associated with increasing R&D scope in high interdependence regimes, especially under high technical uncertainty. In particular, the risk of system obsolescence increases significantly under these circumstances because a failure of one component might cause the development project as a whole to fail.

On balance, we hypothesize that in high interdependence regimes the opportunism reduction potential is small, the benefit of co-specialization is significant, but it is overwhelmed by the obsolescence risk under high technological uncertainty.

Hypothesis 2A: In regimes of high knowledge interdependence, high technological uncertainty is associated with firms having a reduced R&D scope.

We assume identical predictions of both TCE and RBV for regimes of low knowledge interdependence. What differs is our assessment of the relative weight of the factors due to changes in knowledge interdependence. The TCE perspective would again call for increasing R&D scope as a response to increasing technological uncertainty. Since a low interdependence regime comes close to the assumption of component independence we conjecture that the opportunism reduction potential in this regime is substantial.

Because components can be viewed as simply additive in the low interdependence regime, the risk of system obsolescence as a result of component failure is substantially reduced. Similarly, the second argument from the RBV perspective for increasing R&D scope to achieve higher system performance is unconvincing if relative component independence is assumed.

In summary, while the system performance benefits from increasing R&D scope remain low in low interdependence regimes, even under high technological uncertainty, the benefit of integration through opportunism reduction is significant, especially under high technological uncertainty. Hence, our third hypothesis:

Hypothesis 2B: In regimes of low knowledge interdependence, high technological uncertainty is associated with firms having an increased R&D scope.

Insert Table 1 about here

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3 DATA AND METHODS

3.1 Setting

To test our hypotheses we study the knowledge creation in the automotive airbag industry over 33 years. Automotive airbags are multi-technology products, incorporating diverse technologies such as mechanical, electrical and electronic, computing, chemical, and textile technologies. Hence, they represent a good technological example to study the phenomenon of interdependence of knowledge elements. Below we provide a brief description of the main components of the product and a brief history of the associated industry in the appendix.

An airbag system consists of four main components: inflator, sensor, diagnostic and control unit, and bag. The *inflator, or gas generator*, generates the inflation force necessary to deploy the air bag at very high speed. In the early days of airbag development, pioneering firms such as Eaton Yale and Allied Chemicals experimented with stored inert gas under pressure as inflating medium; later firms began to use explosive inflators – a technology spun off of rocket propulsion technology developed by companies such as Talley Defense Systems, Morton Thiokol, and Rocket Research – for faster bag deployment. The explosive inflator also reduced the size of an airbag system and made it possible to mount it directly in the steering wheel hub (Griswold and Henson, 2003). The *sensor* measures the severity of the car crash impact and works with the control module to discriminate between crash and non-crash events. Early crash sensors were mechanical in which a ball or plate acted as electric switch; later they were replaced by faster and more accurate electronic sensors (Struble, 2003). The *diagnostic and control unit* provides decision capability via complex diagnostic and control algorithms that are implemented in the electronic control unit (ECU). Working together with the crash sensors and inflator, the ECU decides on crash occurrence, explosion timing, and, in newer systems, explosion force (Griswold and Henson, 2003). Finally, the *air bag (or air cushion)* is the actual protective component installed in the steering wheel or dashboard. Early airbags featured neoprene-coated nylon, but the coating was later removed, forcing gas through the fabric pores for better energy dissipation. More recent bag designs also include actual holes and vents to better absorb the occupant energy (Scholz, 2003).

The technical history of the development of automotive airbags in the U.S. began in the 1950s with the first patents granted for devices that could be rapidly inflated to prevent vehicle drivers and passengers from hitting the interior of the automobile in so-called second collisions. Throughout the 1960s a small number of firms worked on the development of a working airbag. The major problem was how to inflate the bag fast enough to inflate it in time for the 'arriving' passenger (less than 50 milliseconds). During the 1960s the solution to employ explosives that were used in rocket propulsion made its way into airbag prototypes. Although the use of explosives as propellant proved to be a critical technical breakthrough, the industry take-off stalled for the next 15 years. From the late 1960s to the mid-1980s, the U.S. government agency tasked with increasing highway safety, the National Highway Traffic Safety Administration (NHTSA), and the major automobile manufacturers fought each other in and outside the courts over the best means to protect drivers and passengers in car crashes. The automobile manufacturers favored active safety devices, e.g., seat belts, over passive ones.[2] In contrast, the NHTSA tried to mandate the introduction of airbags, although unsuccessfully until 1983. As a result, the technical development of airbags for automobiles, as measured in patenting activity, came almost to a halt from the early 1970s to the mid 1980s (Figure 1). Then, in 1983, NHTSA issued a ruling according to which the automobile manufacturers had to introduce passive restraint systems in their vehicles between model year 1987 and model year 1990. This decision, together with several Supreme Court rulings, changes in management in some of the car companies, and pressure from the Insurance industry ended almost fifteen years of court battles (Graham, 1989; Strother, Kanianthra, Morgan, Fitzpatrick and Struble, 2003). During the late 1980s and early 1990s, almost all new passenger cars were equipped first with driver and subsequently with passenger front airbags (Figure 1).

Insert Figure 1 about here

3.2 Data

We approximate firms' knowledge production by using patent data. Although patent data do not capture all innovative activities that firms engage in, patent data does exhibit a close relationship with firms' innovative activities and can be used as a reasonable indicator of knowledge held by those firms (Engelsman and van Raan, 1994; Griliches, 1990; Hall, Jaffe and Trajtenberg, 2002). Each patent is assigned one or more classification numbers based on the technologies the patented invention employs (Hall, *et al.*, 2002), i.e., the classification numbers of a patent correspond to knowledge components used in the invention (Fleming, 2001; Fleming and Sorenson, 2004). Building on this research stream, we use classification numbers as the proxy for technological knowledge components used in a patented invention.

To define the boundary of the airbag industry, we follow recent research and employ sub-class level patent classifications to better define the boundary of a technology when using patent data (Giarrantana, 2004; Rosenkopf and Nerkar, 2001; Stolpe, 2002). After reviewing the manuals of the US patent classification system and the International Patent Classification (IPC) we identify the automotive airbag industry containing the following subclasses: USPC 280/728.1 to USPC 280/743.2 (Table 2).

Insert Table 2 about here

To construct our dataset, we extracted all patents associated with one of the above named airbag categories from Cassis 2 DVD-ROM (USPTO, 2003) that contain all U.S. patents issued between 1969 and 2003. Since there is typically a time lag of two to three years from application to issuing of a patent we focus our analysis on patents applied in the timeframe between 1967 and 2000 to avoid censoring problems. This time frame includes 5,177 airbag patents.

Next, we identified firms who participated in the airbag industry during the focal timeframe. Since firm boundaries change over time through a variety of processes (e.g., mergers and acquisitions or divestments), we collected the firms' history data (e.g., name changes, subsidiaries, spin-offs, acquisitions, mergers, and joint ventures) from databases such as Lexis/Nexis, companies' annual reports (10-K's) and web-sites. Based on these data, we dynamically adjust the assignee codes of the relevant patents. Some (typically small) firms patent their developments but do not really start businesses with them. Such firms typically produce only a few patents sporadically and their impact on subsequent product development in the industry is often insignificant. Since in our data set the top 20 firms account for about 70 percent of the total patents, we focus our analysis on these 20 firms.

3.3 Variables

3.3.1 Dependent variable: R&D scope

As our dependent variable we use airbag-related *R&D scope* of firm *i* in year *t*. Since patent classes have long been used as the proxy for technological components, patent classes in which a firm has patents can be a good proxy for the firm's R&D scope (Fleming, 2001;

Fleming and Sorenson, 2001). We operationalize *R&D scope* of firm *i* in year *t* by the number of patent classes in which firm *i* has patents in year *t*, focusing on the firm's airbag related patents to maintain comparability across firms. We include the number of patent classes in the industry in year *t* as a control.

3.3.2 Independent variable: technological uncertainty

Past research has measured technological uncertainty typically on the project level and often via self-assessment. For example, Raz et al. (2002) asked managers to place their projects in one of four pre-defined categories, from low-tech to super high-tech. Similarly, Song and Montoya-Weiss (2001) measured perceived technological uncertainty with a multi-item scale asking respondents using a Likert-type scale ranging from 0 to 10. In contrast, we develop a dynamic industry-level measure for *Technological Uncertainty,* similar to Luque (2002) and Goerzen (2007). However, whereas Luque and Goerzen measure changes in patenting volume in an industry from year-to-year, we measure technological uncertainty through the changing pattern of the foci of inventive activity over time in our industry. Thus, we operationalize *Technological Uncertainty* in year *t* as the sum of two numbers – the number of patents in year *t* in classes that saw no patenting activity in year *t-1*, and the number of patents in those subclasses that had patents in it in year *t*-1 but did not see any patenting in year *t* – divided by the total number of patents in year *t* [Equation (1)].

$$\begin{aligned} &\mathit{Technological\,Uncertainty} \\ &\equiv \frac{\sum_i (\text{Number of patents in class } i) + \sum_j (\text{Number of patents in class } j)}{\text{Total number of patents in year } t} \qquad (1) \\ &\text{where,} \\ &\qquad i \in \text{Classes which are used in year } t, \text{ but were not used in year } t-1 \\ &\qquad j \in \text{Classes which are not used in year } t, \text{ but were used in year } t-1 \end{aligned}$$

For example, in 1980, 8 classes were newly used, i.e., they had not been used in 1979 (sum of patents in these 8 classes is 11), and 8 classes that were used in 1979 were not used in 1980 (sum of patents in these 8 classes is 13) (Figure 2). Since the total number of patents in the airbag industry in 1980 was 18, the measure of technological uncertainty for 1980 is (11+13)/18 = 1.33. The distribution of technological uncertainty is shown in Figure 3. The significant decline of our measure of technical uncertainty after 1990 could be explained by the emergence of a dominant design (Utterback, 1994), i.e., the general knowledge structure underlying automotive airbags stabilizes. Since a firm's R&D scope in year *t* might be decided based on the technological uncertainty in previous years, we include lagged variables reflecting technological uncertainty from year *t-1* to *t-4*.

Insert Figure 2 and Figure 3 about here

3.3.3 Moderating variable: knowledge interdependence

In the literature, the concept of interdependence has been measured through various metrics. For example, economist have used the construct of complementarity between business functions and practices (Milgrom and Roberts, 1995), and management scholars have interpreted self-perceived complexity assessments of products and processes as metrics for interdependencies among a firm's productive activities (Lenox, *et al.*, 2010). Since our focus is on inventive activities we build on a measure for interdependence developed by Fleming and Sorenson (2001; 2004), albeit introducing a subtle but important difference. Similar to Fleming and Sorenson, and others, e.g., (Engelsman and van Raan, 1994), we use the co-occurrence of patent subclasses on a patent as an indicator of some sort of coupling between knowledge components (which may or may not coincide with physical components). However, whereas Fleming and Sorenson design their measure to be interpreted as a proxy for ease of recombination of patent classes, we strive to measure the knowledge interdependence on an industry-level in year *t*. We interpret our measure of knowledge interdependence as the interconnectedness of technical areas required for successful inventions.[3] This interconnectedness is dynamic, i.e., fluctuates over time, and represents an aspect of the underlying knowledge structure faced by all firms. As such, our measure differs from product-focused measures (Fixson and Park, 2008) that can exhibit – at least temporarily – interfirm differences, and thus should be taken at the firm-level. Similarly, it also differs from firm-specific measurements of the connections between product knowledge, organization, and production process (Brusoni and Prencipe, 2006).

We use a two-step procedure to construct our knowledge interdependence measure: first, we calculate the strength of interdependence between two knowledge components as the number of co-occurrences of two patent classification codes, and normalize it by the number of patents in those two classes [Equation (2)]. The maximum of our pair-wise interdependence is 1 (i.e., all patents are put in both classes), and the minimum is 0 (i.e., no patent is put in both classes).

$$\begin{aligned}&\text{Pair-wise interdependence between class } i \text{ and class } j\\ &\equiv l_{i,j} = l_{j,i} = \frac{\text{Number of patents having both class } i \text{ and class } j}{\sqrt{(\text{Number of patents in class } i)(\text{Number of patents in class } j)}}\end{aligned} \qquad (2)$$

To calculate the industry-level knowledge interdependence, we sum up all pair-wise interdependences and divide the sum by the maximum number of pair-wise links. If there are N knowledge components in a system, the maximum number of pair-wise link is N•(N-1)

[Equation (3)]. Hence, our measure of interdependence can be interpreted as the weighted number of pair-wise links in a system.

$$Interdependence \equiv I = \frac{\sum_{i,j} l_{i,j}}{N \cdot (N-1)} \qquad (3)$$

Where, $i \neq j$ and N is the number of components

For illustration, consider the year 1980 in our data set (see pair-wise interdependence between knowledge components and their strength in Figure 4). The knowledge that got patented in the airbag Industry in 1980 was composed of 15 knowledge components. Of these, 7 components were linked with each other, 6 components had only a pair-wise link, and 1 component had no link with other components.[4] Consequently, system-level knowledge interdependence in 1980 was 0.109 (= 2•(1+0.45+…) / (15*14)). Figure 5 shows the distribution of knowledge interdependence over time.

Insert Figure 4 and Figure 5 about here

To investigate how the relationship between technological uncertainty and R&D scope changes in regimes of high knowledge interdependence and low knowledge interdependence, we include dummies indicating high and low interdependence. The *interdependence dummy* in year t is set to high (1) if interdependence in year t is larger than the average value of interdependence over our study period and set to low (0) if smaller than the average over that time period.

3.3.4 Control variables

Number of total patent classes in the industry in year *t*: Since the number of patent classes in which a firm has patents can grow with the increase of available classes in the industry rather than as a response to changing uncertainty, we include the number of patent classes in the industry in year *t* to control for this effect.

Position in supply chain: Although we focus in our analysis on one industry, its participants are not all identical. Research on the automobile industry has shown that the type of relationship between original equipment manufacturer (OEMs) and its suppliers impacts the R&D scope of both OEM and supplier (Helper, 1991). We include dummies to distinguish between OEMs (0) and suppliers (1).

Region: Firms in a certain region may build specialized knowledge in a certain set of technological fields because of geographic knowledge localization (Jaffe, Trajtenberg and Henderson, 1993; Krugman, 1991). We include geographic location dummies, determined by the region of a firm's head-quarter to account for this potential bias: U.S. (0), Europe (1), and Japan (2).

3.4 Model Specification

Since our dependent variable is an overdispersed count variable, we specify a negative binomial distribution to accommodate the overdispersion in our data (Cameron and Trivedi, 1998; Hausman, Hall and Griliches, 1984). Moreover, in situations in which measurements are repeated over time on the same subjects, correlations between observations must be considered (Dobson, 2002). The Generalized Estimating Equations (GEEs) regression method is increasingly used in contemporary research (Ahuja and Lampert, 2001; Katila and Ahuja, 2002) to accommodate correlations between observations. In summary, our regression model is a GEE model with a negative binomial distribution [Equation (4)].

$$y = \mu + \beta_1 X_1 + \beta_2 X_2 + \beta_3 (X_1 \times X_3)$$

where y : R & D scope of a firm

X_1 : Technological uncertainty

X_2 : Interdependence

$$X_3 : \begin{cases} 0, \text{ if interdependence is high} \\ 1, \text{ if interdependence is low} \end{cases}$$

$$y = \begin{cases} \mu + \beta_1 X_1 + \beta_2 X_2, \text{ if interdependence is high} \\ \mu + (\beta_1 + \beta_3) X_1 + \beta_2 X_2, \text{ if interdependence is low} \end{cases} \quad (4)$$

4 EMPIRICAL RESULTS

Table 3 presents descriptive statistics and Table 4 contains the estimated coefficients for the GEE regression models. In our models, we include *technological uncertainty* subsequently from year *t-1* to *t-2* (we also tested longer time lags but found them insignificant, see appendix for details), *interdependence,* and the interaction term of *interdependence dummies* with *technological uncertainty* to test our hypotheses (models 1 to 3). Across models 1 to 3, lags of technological uncertainty show negative and significant ($p<0.05$) coefficients. *Interdependence* has a positive and significant ($p<0.05$) coefficient, which means that firms are more likely to integrate when interdependence is high. Interaction terms of *interdependence dummies* with one-year lagged *technological uncertainty* obtain significant ($p<0.05$) coefficients (model 1 and model 2). The interaction terms become insignificant ($p<0.05$) when we add the interaction of *interdependence dummy* with two-year lagged *technological uncertainty* (model 3). This effect suggests that the consideration of the interaction effect of interdependence and the previous year's technological uncertainty is meaningless. Moreover, model 2 shows the highest log-likelihood of all three models. Therefore, we use model 2 to discuss the results of our hypotheses tests below.

In model 2, the interaction term of technological uncertainty and low interdependence exhibits a positive and significantly ($p<0.05$) different coefficient from that in high interdependence. This result suggests that the moderating effect of interdependence is significant, which supports our Hypothesis 1. The sum of the coefficients of technological uncertainty and of the interaction term represents the relationship between technological uncertainty and R&D scope in high and low interdependence regimes. In model 2, this sum is negative and significant ($p<0.05$) under high interdependence, which fully supports our Hypothesis 2A. However, that sum is also negative and significant in low interdependence. Although the direction of the interaction effect is the same as we hypothesized, the size of the coefficient of the interaction term in low interdependence regimes is not large enough to reverse the sign of the coefficient of technological uncertainty. This result only partially supports our Hypothesis 2B. We discuss our interpretation of this partial support below.

Finally, we report the coefficients of our control variables. The number of classes in the industry has a positive and significant coefficient ($p<0.05$) only in model 1. The coefficients of all other control variables (position in supply chain and region are insignificant ($p<0.05$).

Insert Table 3 and Table 4 about here

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5 DISCUSSION

We began this article with a discussion of the existing tension between the governance (TCE) perspective and the competence (RBV) perspective on how firms adjust their R&D scope when facing technological uncertainty. To reconcile this apparent contradiction we proposed a model in which the property *knowledge interdependence* – constructed as the inverse of modularity in the knowledge world – moderates the relationship between industry-level *technological uncertainty* and firm-level *R&D scope*. Testing our model with patent data from the U.S. automotive airbag industry we find that the interaction effect of technological uncertainty and high knowledge interdependence is significantly different from that of technological uncertainty and low knowledge interdependence, which confirms our overall model. The results suggest that knowledge interdependence contributes to explaining the difference with which the relationship between technological uncertainty and R&D scope is seen by the two perspectives.

On a more detailed level, the airbag patent data also confirms our prediction of a negative relationship between technological uncertainty and R&D scope in regimes of high knowledge interdependence. This finding is consistent with earlier studies on cognitive limitations of organizations (Levinthal and March, 1993; Nelson and Winter, 1982). In environments in which high levels of technological uncertainty exist, firms can build specialized competencies by focusing on existing knowledge (Prahalad and Hamel, 1990). The data does not confirm, however, our second detailed prediction of a positive relationship between technological uncertainty and R&D scope in regimes of low knowledge interdependence. Instead, we find another negative relationship, albeit a much weaker one compared to the one in high interdependence regimes. We consider it possible that our data – all taken from the domain of knowledge generation – does not show a positive relationship as predicted because it does not really include a very low level of knowledge interdependence such as it can be found in the production domain.

Taken together, our findings have both theoretical and managerial implications. On the theoretical level the results suggest that a systemic knowledge aspect such as modularity – or its inverse interdependence – has a moderating effect on how firms adjust their scope of R&D activities when facing technological uncertainty. In fact, our data suggests that this effect is so significant in the context of knowledge creating activities such as R&D, that the competence perspective can explain our results better than the governance perspective. This supports the call on the TCE perspective to take better into account the possibility that the assumption of unit independence is violated (Williamson, 1999), especially when applied to knowledge-creating settings.

A second theoretical contribution extends modularity theory. Our findings delineate limits to the prediction that low levels of interdependence between components go hand-in-hand with low levels of technological uncertainty, and thus specialization prevails in situations of low technological uncertainty (Sanchez and Mahoney, 1996; Schilling and Steensma, 2001). We bound this argument by stating that it can be the inherently higher degree of interdependence of knowledge-generating activities that leads firms to be integrated even at low levels of technological uncertainty and even though they become specialized in the production domain (Brusoni, *et al.*, 2001; Granstrand, *et al.*, 1997; Takeishi, 2002).

A third contribution is empirical. In contrast to extant research mostly focusing on firms' defensive moves in existing industries as a response to an external competitive shock via a technological innovation (Henderson and Clark, 1990; Wolter and Veloso, 2008), our study investigates knowledge creation activities and the corresponding scope decisions in an emergent industry, thus extending our knowledge by including the emergence of the innovations themselves.

Our analysis is descriptive, not normative. In other words, we cannot claim that our observations of firms' choices on R&D scope directly affected the firms' performance. Financial performance data is impossible to obtain if the unit of analysis (airbags) is only a fraction of the business of the firms under consideration. No firm in our sample reports separately financial results of its airbag-related business. For the same reason we could not collect targeted input data such as R&D dollars, that perhaps would allow imputing some measure of R&D efficiency. However, what we can say is that our focal firms are the most innovative firms in this industry in terms of the size of their knowledge pool, i.e., airbag patents (and probably in terms of the value of their knowledge pool). Consequently, our results may at least indicate the minimal conditions for successful R&D in the airbag industry.

With this limitation in mind, managers can use our findings to guide their strategic decisions about the R&D scope when facing different levels of technological uncertainty. By nature, R&D activities involve a significant risk for returns from investments. The risk is especially high under high technological uncertainty, which makes the failure of developments more probable, and under high interdependence, which increases the threat of system obsolescence in case of a component failure. Under such conditions, firms are better off focusing on a narrower set of technological fields, i.e., their core competence areas, to increase the performance of their R&D.

6 CONCLUSION

The boundaries of the firm are a fundamental issue in the theory of the firm, and the R&D scope of the firm is a special case of this question. Traditionally, the R&D boundary of a firm has been thought of as a 'make vs. buy' decision similar to decisions in the world of production. In contrast, we suggest that the effect of knowledge interdependence on the relationship between technological uncertainty and R&D scope is significant, and because R&D is by nature more interdependent with the development of other knowledge components than production is, the benefits of co-specialization are relatively large. On the other hand, high levels of technological uncertainty can cause the cost of integration to overwhelm its benefits. Consequently, our theories to predict the location of firm boundaries when taken from the world of production and transferred to the world of R&D should be adjusted. Similarly, firms should consider the interdependence of knowledge components in their decision about their R&D boundaries.

There are at least three possible limitations to our study. First, our finding does not produce details on the nature of the R&D scope change. Since we measure the R&D scope by using the number of patent classes as a proxy, we do not know whether a firm increases into or decreases from specific knowledge components. Second, the direction of interdependence is not considered, our measure simply assumes that the dependence is symmetric. Third, patent data in general track only some inventions but not all of them. For example, process innovations that are not patented are not accounted for in our data set, but these innovations still require active attention of the R&D management.

We see two directions for future research. The first is to test our model in other industries. We assume that interdependence is an industry-level phenomenon; thus, it is possible that the effect of interdependence is more significant in some industries and weaker in others. The second interesting extension of this research would be the exploration of R&D scope change and interdependence in more detail, for example by investigating pair-wise interdependence of components rather than interdependence at the system level.

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[1] Our description here occurs with broad strokes. The conceptualizations of resource, capability, and knowledge are of course not identical. While research has produced finer delineations – Makadok (2001), for example, shows when resources and capabilities are substitutes and when they are complements – for the discussion here the major point is that this group is collectively relatively clearly distinguishable vis-à-vis the transaction cost economics perspective.

[2] The terms 'active' and 'passive' are somewhat misnomers here with respect to the technology. 'Passive' refers here to safety systems that would work without requiring any activity from drivers or passengers; thus it is the passengers who could remain 'passive.' Conversely, 'active' safety systems required some action from the user, for example, a manual belt required the user to manually "buckle up."

[3] We assume here that inventions that are granted a patent are technically successful. We make no statement about the inventions' potential or actual commercial success.

[4] To improve readability of Figure 4 we exclude patent class 280 because due to our sampling strategy, class 280 is listed on all patents in our sample, and consequently exhibits interdependence will all other classes.

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Appendix: Testing the influence of Technological Uncertainty

To test how rapidly the firms in the industry respond to changes in technological uncertainty, we include *technological uncertainty* subsequently from year *t-1* to year *t*-4 and run the regressions (Table 5). In model A, we include only year *dummies* to check for time dependencies. 17 *year dummies* show significant coefficients (1971 to 1973 and 1987 to 2000). Those years correspond to years with relatively low uncertainty. Thus, this significance may come from the change of technological uncertainty rather than from other unobserved factors, e.g., governmental regulation.

In models B through E, we include *technological uncertainty* subsequently from year *t-1* to year *t-4* and add other control variables. The first two lags of technological uncertainties obtain negative and significant ($p<0.05$) coefficients. Three- and four-year lagged technological uncertainties obtain negative but insignificant ($p<0.05$) coefficients. These regression results suggest that the firms in this industry adjust their R&D scope quite quickly (within one or two years) as a reaction to changes in technological uncertainty. Consequently, we include only the first two lags of technological uncertainties in our models to test our hypotheses.

Insert Table 5 about here

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7 TABLES & FIGURES

Table 1: Summary of hypothesized relationships

	Knowledge Interdependence			
	Low		High	
	Technological Uncertainty		Technological Uncertainty	
	Low	High	Low	High
TCE	Reduced	Increased	Reduced	Increased
RBV	Increased	Reduced	Increased	Reduced
Modularity	Reduced	Reduced	Increased	Increased

Table 2: U.S. patent class/subsclasses relevant for automotive airbags

Level 1	Level 2	Level 3	Title
280/728.1			Inflatable passenger restraint or confinement (e.g., air bag) or attachment
	280/728.2		With specific mounting feature
	280/728.3		Deployment door
	280/729		Plural compartment confinement (e.g., "bag within a bag")
	280/730.1		Inflated confinement specially positioned relative to occupant
		280/730.2	Mounted in vehicle and positioned laterally of occupant
	280/731		Deflated confinement located within or on steering column
	280/732		Deflated confinement located in or on instrument panel
	280/733		In the form of or used in conjunction with a belt or strap
	280/734		Responsive to vehicle condition
		280/735	Electric control and/or sensor means
	280/736		With source of inflation fluid and flow control means thereof
		280/737	With means to rupture or open fluid source
		280/738	With means to aspirate ambient air
		280/739	With confinement deflation means
		280/740	With means to diffuse inflation fluid
	280/741		Inflation fluid source
	280/742		Flow control means
	280/743.1		Specific confinement structure
		280/743.2	With confinement expansion regulating tether or strap

Table 3: Descriptive statistics

				Pearson Correlation Coefficients, N=528						
		Mean	Std. Dev.	1	2	3	4	5	6	7
1	R&D Scope	3.326	3.686	1						
2	Technological uncertainty (t-1)	0.629	0.587	-0.5 ***	1					
3	Technological uncertainty (t-2)	0.653	0.578	-0.48 ***	0.792 ***	1				
4	Technological uncertainty (t-3)	0.675	0.568	-0.43 ***	0.691 ***	0.787 ***	1			
5	Technological uncertainty (t-4)	0.689	0.557	-0.37 ***	0.567 ***	0.677 ***	0.777 ***	1		
6	Interdependence (Continuous)	0.22	0.084	0.216 ***	-0.11 **	-0.18 ***	-0.17 ***	-0.3 ***	1	
7	Interdependence (High/Low)	0.353	0.478	0.189 ***	-0.14 ***	-0.19 ***	-0.17 ***	-0.23 ***	0.866 ***	1

(Significance code: 0 '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 ' ' 1)

Table 4: GEE regression coefficients predicting firms' R&D scope

	Estimates					
Parameter	Model 1		Model 2		Model 3	
Intercept	0.888	***	1.310	***	1.334	***
Technological Uncertainty(t-1)	-1.121	***	-0.918	**	1.047	***
Technological Uncertainty(t-2)			-0.520	**	-0.360	**
Interdependence(t-1)	2.107	***	1.402	***	1.347	***
Technological Uncertainty(t-1)* Interdependence(High)	0.000		0.000		0.000	
Technological Uncertainty(t-1)* Interdependence(Low)	0.378	***	0.329	***	0.479	
Technological Uncertainty(t-2)* Interdependence(High)					0.000	
Technological Uncertainty(t-2)* Interdependence(Low)					-0.173	
# of Classes in the Industry	0.043	**	0.030		0.028	†
Supply Position(Supplier)	-0.129		-0.130		-0.128	
Supply Position(OEM)	0.000		0.000		0.000	
Region(Japan)	-0.181		-0.201		-0.209	
Region(Europe)	-0.068		-0.025		-0.037	
Region(U.S.)	0.000		0.000		0.000	
Scaled Deviance	0.938		0.935		0.933	
Log Likelihood	233.26		236.04		235.11	

(Significance code: 0 '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 ' ' 1)

Table 5: GEE regression coefficients testing the influence of technological uncertainty

Parameter	Estimates								
	Model A	Model B		Model C		Model D		Model E	
Intercept		1.423	***	1.727	***	1.686	***	1.691	***
Technological Uncertainty(t-1)		-0.825	***	-0.634	***	-0.535	***	-0.527	***
Technological Uncertainty(t-2)				-0.606	***	-0.469	*	-0.455	*
Technological Uncertainty(t-3)						-0.265	†	-0.259	†
Technological Uncertainty(t-4)								-0.034	
# of Classes in the Industry		0.037	**	0.022		0.033		0.033	
Supply Position(Supplier)		-0.114		-0.120		-0.121		-0.121	
Supply Position(OEM)		0.000		0.000		0.000		-	
Region(Japan)		-0.165		-0.192		-0.202		-0.202	
Region(Europe)		-0.027		0.006		-0.024		-0.023	
Region(U.S.)		0.000		0.000		0.000		0.000	
Year Dummies	17 Years(p<0.05)								
Scaled Deviance	0.998	0.951		0.944		0.939		0.940	
Log Likelihood	475.12	233.11		236.92		235.52		235.15	

(Significance code: 0 '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 ' ' 1)

Figure 1: R&D activity and sales in the automotive airbag industry

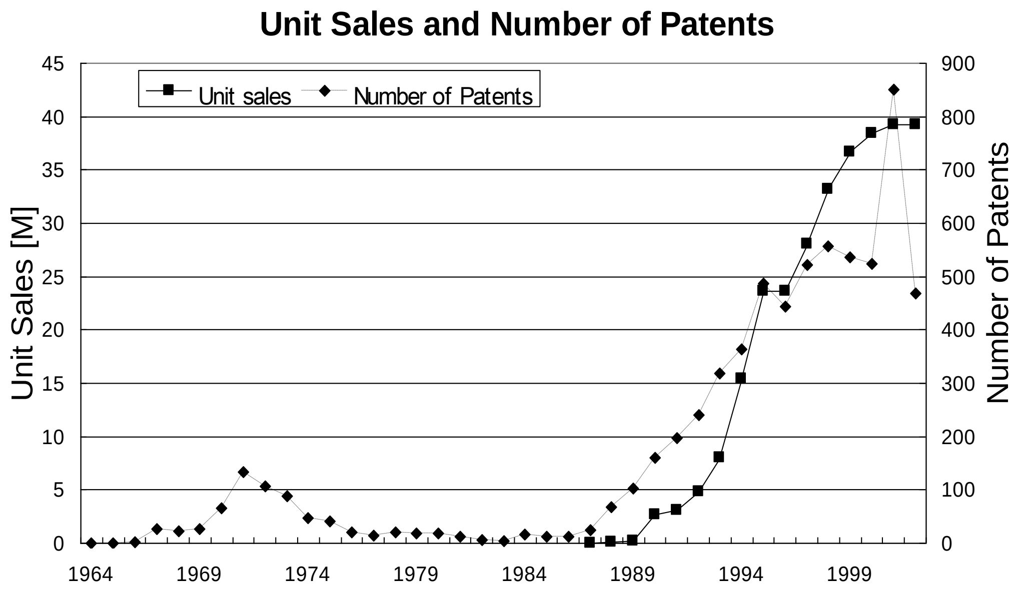

Figure 2: Distribution of 46 patent classes associated with airbag-related patents

Classification Number	1967	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983
55			3						3	2					1		
102	3	3	3	9	12	15	11	6	9	2	7		1	3	1		
149					9		12		4					2			
222	2			14	26	15	13	8	5		2		3				
252							6		5								
422		4	3	5	12	9	10	5	5	2	2		1	2	3		
423									4								
516																	
340						7	5	6		3	1			2	2	2	
367														1			
701														1		1	
200	3	4	3	6	11	15	8			3	1	4	2	2	1		
439												2					
73											1		1				
324																	
60							9										
310														1			
323																	
361											1						
219													1				
307																	2
141				4	9								1				
241																	
264														1			
493													2				
29																	
92																	
114													1				
180	5	2	3	8	20	21	10	9	6	2	4	7	1	5	2	3	1
244													1	3	1		1
280	27	23	27	65	134	106	89	48	41	21	15	21	19	18	13	6	5
293						6											
296																1	
0																	
49															1		
74	2		2											1	1	1	
285										2							
403																	
116															2		
137			2	10	28	16	7	9	4		2		3				
138												2					
182					8												
206															1		
297							8	6	3		1		1	3			1
428											1			2			
441													1		1		

Classification Number	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
55																	
102	2	2	2	3	7	10	16	13	15	28	35	38	36	32			
149	2	2	1	2	6												
222	1		1						17			30	25				
252		1															
422	3	2						12		18	21						
423	2																
516	1																
340		2	2		10	20	19	23	23	34	39	38	28	31	44		45
367																	
701						8		14	18	19	38	28	29	48	81	64	77
200			1		4	7			13	19		30	23				
439																	
73			2		4												
324			1														
60																	
310																	
323			1														
361																	
219																	
307				3	11	17	15	22	22	31	41	31	25	33	29		
141																	
241		1															
264																	
493																	
29		1															
92	1																
114																	
180	3	2	4	3	13	18	25	37	36	50	51	50	48	68	77	68	89
244	3			2													
280	17	12	13	24	67	103	160	197	240	319	364	486	443	521	543	507	483
293																	
296	1																
0	1																
49																	
74				5													
285		1															
403			1														
116			1														
137	1																
138																	
182																	
206																	
297	2	1	1														
428																	
441	1	1															

Figure 3: Intertemporal distribution of technological uncertainty

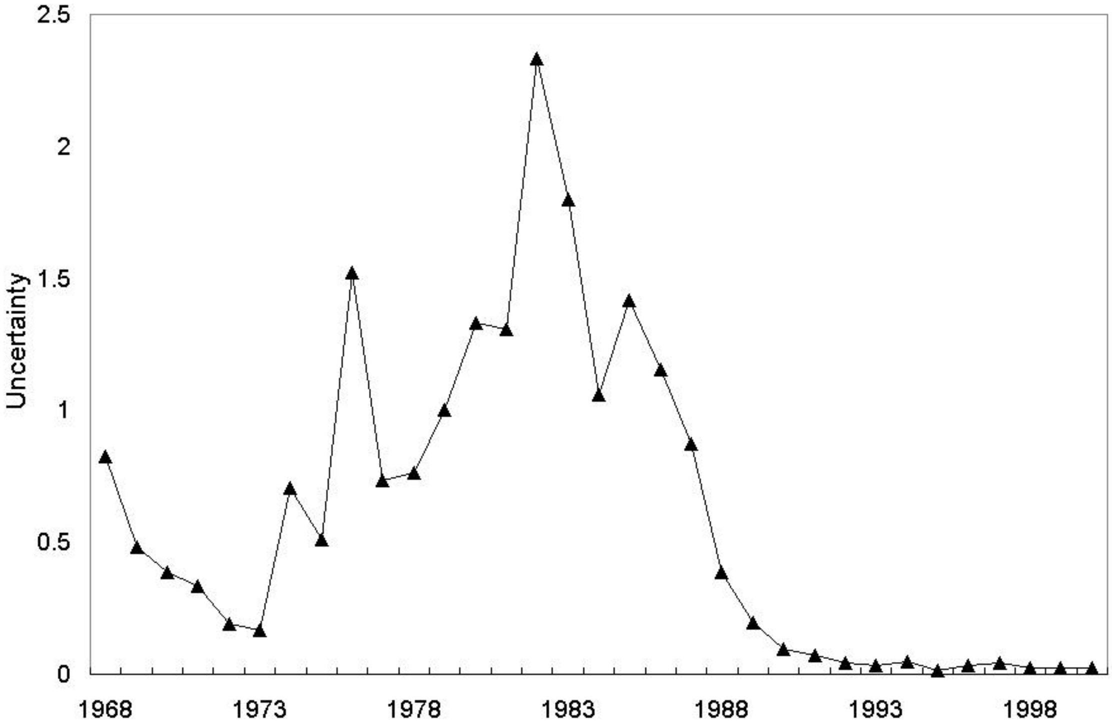

Figure 4: Pair-wise interdependence among knowledge components in 1980

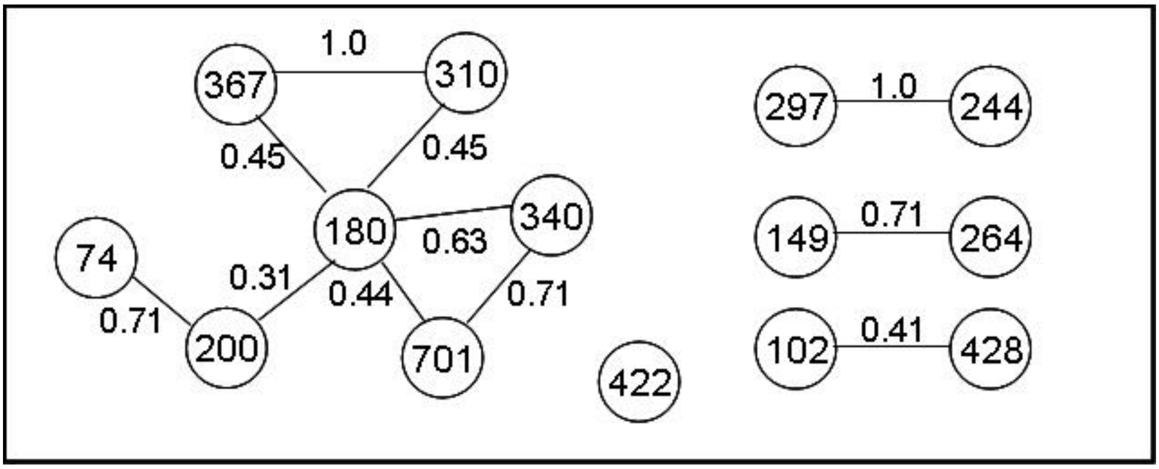

Figure 5: Distribution of knowledge interdependence in the automotive airbag over time