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Intra-Organizational Integration and Innovation: Organizational Structure, Environmental Contingency and R&D Performance

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ABSTRACT

It is widely thought that intra-firm integration has a positive effect on organizational performance, especially in environments characterized by complex and uncertain information. However, counter arguments suggest that integration may limit flexibility and thereby reduce performance in the face of uncertainty. Research and development activities of a firm are especially likely to face complex and uncertain information environments. Following prior work in contingency theory, this paper analyzes the effects of intra-organizational integration on manufacturing firms' innovative performance. Based on a survey of R&D units in US manufacturing firms and patent data from the NBER patent database, we examine the relation between mechanisms for linking R&D to other units of the firm and the relative innovativeness of the firm. Furthermore, we argue that the impact of integration may vary by the importance of secrecy in protecting firms' innovation advantages. We find that intra-firm integration is associated with higher self-reported innovativeness and more patents. We also find some evidence that this effect is moderated by the appropriability regime the firm faces, with the benefits of cross-functional integration being weaker in industries where secrecy is especially important. These results both support and develop the contingency model of organizational performance.

KEYWORDS: Innovation; Organizations; Contingency theory

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1. Introduction

As firms become larger and their markets expand, the internal division of labor becomes increasingly important. As Adam Smith noted at the beginning of the industrial era, the division of labor is critical for increasing returns in the modern economy. An increasing division of labor creates the advantages of specialization and the associated accumulation of skills and productivity gains from deeper learning by doing and experimenting (Foss, 2001; Simon, 2002). However, according to Simon (2002), "all complex organizations are nearly decomposable" implying that the components are still interdependent although they are specialized in a division of labor. Foss (2001) argues that an increase in the division of labor can cause greater complexity and uncertainty, hampering coordination of the specialized and interdependent tasks and thereby resulting in "problems of bottlenecks and problems from uneven development of components". Therefore, specialization in organizations creates the need to account for the interdependencies within the organization in order to ensure smooth operation of the whole. This problem is exacerbated in a modern knowledge-based economy that is continually seeing the emergence of new, complex technologies, new products and new markets, so that strict specialization of functions in an organization may cause inefficiency and ineffectiveness in organizational performance. The marketing, R&D, and production departments in a company, all of which have different objectives traditionally, need to cooperate with one another to develop and introduce innovations (Burns and Stalker, 1961). Increasing product complexity and complex development processes require firms to integrate knowledge from diverse, specialized subunits (Emmanuelides, 1993). However, conflicts between an R&D lab with a long-term goal of developing cutting-edge technology and eager to apply the latest technology for products and a marketing department with a short-term goal of gaining quick profits and pursuing incremental modifications of products matching the demands of buyers can prevent responsiveness to rapid changes of the market and prevent mutually beneficial decision making (Burns and Stalker, 1961; Lawrence and Lorsch, 1967a; Dougherty, 1992). Furthermore, complex, interdependent modern technology often requires detailed, and sometimes tacit, knowledge to operate efficiently, and such knowledge needs to be generated and transmitted through coordination among different work units (Chuma, 2006). Therefore, managing specialization and coordination simultaneously is critical for organizational performance.

Prior work suggests that integrating distinct but interdependent organizational units may be key to promoting effective performance, especially for generating rapid innovation (Burns and Stalker, 1961; Lawrence and Lorsch, 1967a; Van de Ven et al., 1976; Clark et al., 1987; Hage et al., 2008; Liu, 2009). Building on this literature, this paper presents data on the effects of integration on U.S. manufacturing firms' innovative performance, measured by self-reported innovativeness and granted patents. Furthermore, we consider the effects of organizational environment as an additional contingency for the effect of integration on organizational performance. In particular, while information sharing may be key to improving integration, secrecy can also be a key component of firm appropriability strategy, although the importance of secrecy varies by industry (Cohen et al., 2000). Thus, we test to see if the effect of integration varies by the importance of secrecy in an industry. Based on data from the Carnegie Mellon survey of R&D managers and the NBER patent database, we find that for manufacturing firms in the U.S., the strength of inter-departmental integration has a significant positive effect on organizational innovative performance. However, we also find that this effect differs depending on the importance of secrecy in the innovation process.

In Section 2, we discuss theoretical and empirical background and our hypotheses.

Section 3 describes the dataset and variables. Section 4 presents the results. Section 5 discusses the implications of our findings.

2. Contingency Theory and Innovation Performance

Lawrence and Lorsch (1967a, 1967b) define differentiation as "*the difference in cognitive and emotional orientation among managers in different functional departments*" or "*the status of segmentation of the organizational system into subsystems with particular attributes related to its relevant external environment (i.e. the formal division of labor)*", and integration as "*the quality of the state of collaboration that exists among departments that are required to achieve unity of effort by the demands of the environment.*" In this paper, taking into account Lawrence and Lorsch's definition, we focus on functional differentiation (specialization) and integration, i.e., coordinating the different functional units through various integrating structures. A key finding of contingency theory is that the optimal level of integration is contingent on the level of differentiation. The expansion of organization size generates functional and structural differentiation with an increasing number of components, which creates pressure for coordination (Blau, 1970). However, it is costly to coordinate specialized subunits because the greater structural differentiation leads to greater inter-subunit heterogeneity and higher intra-subunit homogeneity (Child, 1972). Therefore, the effect of integration on organizational performance can vary by the level of differentiation, because organizations with higher differentiation require coordination more than those with low differentiation. Expanding on this and focusing on product components' specificity and decomposability rather than an organization's structural differentiation, recent work by Antonio et al. (2009) shows how the effect of internal integration varies in high and low product modularity, which is defined as “separateness, specificity and transferability of product components in a product system” (Antonio et al., 2009). Also, taking into consideration the increasing complexity and uncertainty, Foss (2001) reiterates and sharpens Coasian price coordination by emphasizing the importance of managed coordination. He emphasizes the importance of managed coordination over price coordination because of the “inability to specify future states of the world” and the appearance of “new unknown interdependencies between tasks and endogenous technological uncertainty by an increasing division of labor” (Foss, 2001). Thus, we see that specialization combined with uncertainty puts strains on organizational functioning and increases demands for coordination of heterogeneous but interdependent units.

Integrating diverse functional units has been shown to help improve coordination and overcoming some of the difficulties generated by specialization, although the optimal level of coordination varies by the nature of the knowledge being shared and by the environmental uncertainties the organization faces (Lawrence and Lorsch, 1967a; Hansen, 1999). Prior studies of innovation have shown that integration contributes to firm development through combining diverse knowledge, narrowing the gap between functionally different work units such as marketing, production and R&D groups, and reduces project completion time producing higher quality products and satisfying their customers more than the less-integrated system (Clark et al., 1987; Fujimoto, 1989; Iansiti and Clark, 1994; Rondeau et al., 2000). For example, Clark et al. (1987) analyze differences in R&D performance among Japanese, U.S. and European auto firms based on project strategies and organization. Their study shows that high specialization can cause disconnects among work units as well as wasted time because it requires time for workers to understand each other’s work and generates difficulties in coordination and mutual adjustment. They find that Japanese auto companies are more integrated and less specialized than their American and European counterparts and also spend fewer hours to complete their projects whereas the U.S. and European auto companies use relatively weak integrative devices even though they are more specialized than the Japanese. Moreover, integration is also critical for technology commercialization by developing cross-functional skills and combining different functions necessary for technology commercialization (Zahra and Nielsen, 2002). Some companies can succeed in technology commercialization with limited resources but effective integration while others can fail due to a lack of effective integration despite abundant resources (Ettlie, 1988; Song et al., 1997). These prior studies suggest that maximization of benefits from functional diversity can be achieved by generating consensus through collaborative communications, negotiation, and integrative activities (Lovelace et al., 2001). Integration (through such mechanisms as interdepartmental committees, cross-functional teams, or on-line forums) provides a locus for members in functionally different units of an organization to congregate and strive to solve problems in concert (Nonaka and Konno, 1998).

The importance of integrating functionally differentiated units is also highlighted by arguments about the importance of open innovation (Chesbrough, 2003). In less uncertain environments, organizations may be able to develop their new products in the simple sequential model which consists of “planning for an entire product”, “a specific new product program”, “feature-cost tradeoffs”, “technical specifications”, and “pre-production and ramp-up” (Nemetz and Fry, 1988; Gerwin, 1993). This simplified process does not strongly depend on joint participation of R&D, marketing and production units in product development. However, the continuous evolution of knowledge creates technological complexity and interdependence among actors’ diverse knowledge and skills for completing the final project (Rosenberg, 1976; Nelson, 2003; Zhong and Ozdemir, 2010). Therefore, a more uncertain and complex environment increases the need for organizations to manage their environment through integrative activities across different functional units (Nemetz and

Fry, 1988; Berends et al., 2007). This need for integration can include the need to incorporate input from suppliers and customers into the innovation process (Von Hippel and Von Hippel, 1988, Chesbrough 2003; Von Hippel, 2005). Ettlie (1995) argues that a changing competitive environment with high uncertainty, complexity, and flexibility requires integration among different disciplines and functions. Moreover, intra-organizational, multifunctional teamwork can reduce internal transaction costs, increasing efficiency (Ettlie, 1995). Therefore, in the face of high information complexity and uncertainty (as is the case for R&D units), integrating functionally different parts of an organization should increase performance.

On the other hand, integration may have negative effects on innovative performance under constraints of bureaucracies and structured organizational routines (Rogers, 1995). If innovation is closely watched by a variety of departments with different interests and has to adhere to the expectations of various audiences, truly innovative ideas may be squashed before they can stand on their own. Rogers (1995) emphasizes the potential of "skunkworks"[1], or independent R&D, using examples of the development of the P-80 Shooting Star fighter jet and the Macintosh computer. Rich (1994) claims that skunkworks are more effective for small programs than large programs because they are risking a smaller budget, but that they are most effective as part of a large entity to be able to access the larger resource as necessary. Skunkworks can elicit creativity not constrained by convention, procedure, rules and routines (Rich, 1994; Fosfuri and Rønde, 2009). Moreover, Fosfuri and Rønde (2009) argue that skunkworks, isolated from the large entity (i.e., weakly intergrated R&D units), can lead to a more radical research trajectory, avoiding conservative thinking by internal competition between an R&D unit and other units, whereas R&D units

[1] "Skunkworks" or "Skunk Works" originated from Lockheed's (a developer of the P-80 Shooting Star) secret research and development projects named after the "Skunk Works" factory in Al Capp's Li'l Abner comic strip and representing geopolitically and psychologically independent groups (Rich, 1994; Rogers, 1995; Bommer et al., 2002).

that are tightly integrated are more likely to choose an incremental research trajectory with low risk. Skunkworks, however, can generate difficulties for collaboration and coordination between an R&D project team and other units leading to an increase in costs for integrating radical innovation by an R&D unit into the large entity (Fosfuri and Rønde, 2009).[2] Furthermore, Fosfuri and Rønde (2009) find that exploitation by R&D units in integration with other units can also engender exploration if R&D units are capable enough, suggesting that integration may not reduce creativity.

Thus, we have arguments suggesting offsetting hypotheses on the effects of integration on R&D performance:

HYPOTHESIS 1a: *Integration improves innovative performance due to information sharing and coordinated development*.

HYPOTHESIS 1b: *Integration limits innovative performance due to bureaucratic constraints on R&D creativity.*

If hypothesis 1a is true, the effects of integration on improving performance should be even stronger in more differentiated organizations, either those that span industries, or in larger organizations, which we expect to be more differentiated (Blau, 1970).

Furthermore, we expect that the effect of integration will not be constant in every organization because organizations operate under different environmental conditions. As

[2] Integration also requires different types of maintenance costs. Hansen (2002) raises the concern that while direct relations (i.e., short network paths) among different units accelerate transfer of tacit knowledge and help incorporate knowledge from other units to finish the project, they require maintenance costs with their associated distractions from tasks and are not necessary when codified knowledge is used for the project, thereby slowing the project completion time in such cases.

Lawrence and Lorsch (1967a) addressed in their work, organizations under different environmental conditions benefit from different internal characteristics and abilities to deal with those conditions effectively, that is, the relation is *contingent*. Optimal organizational structure can vary by environment, technology, and size (Lawrence and Lorsch, 1967a; Blau, 1970; Woodward, 1970; Child, 1972; Woodward et al., 1994). Child (1972) suggests that "environmental variability" (i.e. uncertainty), "environmental complexity", and "environmental illiberality" (i.e. the degree of decision-makers' discretion) influence the optimal choice of organizations' structural forms. Tidd (2001) argues that uncertainty and complexity are two key environmental contingencies that account for variation in organizational configuration and performance. Our first hypotheses test the effect of organizational structure (i.e., an R&D unit's integration with other functional units) on its innovative performance under conditions of uncertainty (i.e., rapid change of technology) and complexity (i.e., technological and organizational interdependency) as environmental constraints (Burns and Stalker, 1961; Lawrence and Lorsch, 1967a; Thompson, 1967; Tidd, 2001). We can think of this as the first-level contingency hypothesis (in environments characterized by high uncertainty and complexity, integration is key for performance). However, in the R&D context, in addition to the need to integrate across functional units, secrecy is also often important for maintaining appropriability of the rents from innovation, to prevent copying and to maintain lead time advantages (Cohen et al., 2000). Thus, moving beyond the traditional contingency theory arguments, we develop contingency theory by considering another environmental constraint, that is, the importance of secrecy. We argue that the effect of integration should be contingent on the appropriability regime, in particular, the importance of secrecy. Tacit knowledge, or non-codified knowledge, such as knowhow, is learned by doing and requires inter-personal communication for sharing, and is also often protected by secrecy (Polanyi, 1962; Liebeskind, 1997). In addition, R&D strategy may also require secrecy to maintain lead time advantages. However, while interaction and exchange of knowledge among members in different work units of an organization facilitates transfer of knowledge, involved individuals can obtain knowledge of other team members and expropriate the knowledge, increasing the risk of leaking it to external agents (Liebeskind, 1996; Jaffe, et al., 2000). For example, a recent New York Times article tells the story of Thomas' English muffin (Neuman, 2010). Thomas' strategic advantage was built on a trade secret over the production process. The company compartmentalized the important information about their muffin production process into several pieces to keep it secret and to prevent it leaking out, leaving most production employees and supervisors know only the piece of information directly relevant to their task (low integration). Only seven employees in the whole company knew every step. This created a crisis for the company when a high-level manager (one of the few with complete knowledge) attempted to leave the company and offered to teach rival Hostess the secrets. Only legal action prevented the spillover. However, this example shows the potential risks from integration in an industry that depends heavily on secrecy to maintain strategic advantage (in this case, for over 100 years, long after any patents would have expired). Maintaining such secrecy would be very difficult if tight integration led to the knowledge being widely distributed throughout the firm. Unintended disclosure of information can also happen when other units may have links outside the organization, such as between marketing/sales and customers or production and suppliers (Bolton et al., 1994). As Teece (1986) and Liebeskind (1996) argue, a firm requires complementary assets for commercialization of new knowledge and may need the help of external agents as well as internal agents, thereby necessitating exchange of knowledge but deteriorating protection of knowledge. Moreover, secret information is especially vulnerable because competitors can use it if they can legitimately access it, unlike patented information (Seidel and Panich, 1973; Liebeskind, 1997). As Liebeskind (1997) argues, knowledge can be better protected by impeding communication and structural isolation. It, however, increases coordination costs and R&D costs to incorporate knowledge under high secrecy constraints, thereby dampening innovation (Liebeskind, 1997). Therefore, integrating different pieces of information separately belonging to individuals or units (as a result of an effort for protecting knowledge or specialization) is imperative for innovation, but at the same time, enables those involved to identify the final integrated knowledge, and increasing the risk of knowledge spillovers and the potential loss of competitive advantage (Liebeskind, 1996; Rønde, 2001). Based on these arguments, we postulate that organizations need a certain level of integration for innovation, but with the effects of integration varying with the importance of secrecy in their appropriability regime. More specifically, the positive effect of integration can be weaker for industries that use secrecy as their key appropriability mechanism (Cohen et al., 2000). This can be either because in high secrecy industries, units are unwilling to communicate with others even in the same organization (e.g., R&D units' not sharing research plans during interdepartmental committee meeting for fear that sales will leak the information) making integrating structures less productive, or because shared information leaks to competitors leading to loss of lead time (or even being scooped). Thus, our second hypothesis is stated as:

HYPOTHESIS 2. *The relation between integration and innovative performance is dampened for industries where secrecy is a key appropriability mechanism.*

Thus, we are testing two versions of the contingency theory. The first is that, in an environment where uncertainty and complexity (information needs) are high, as is the case for R&D units, integration should improve performance (if the knowledge integration and coordination theories are correct), or may dampen performance (if the independence from bureaucratic control and skunk works theories are correct). Furthermore, we develop a second contingency argument, which is that the impact of integration on performance is dampened in high secrecy environments. We use survey and archival data on R&D unit structures and performance to test these hypotheses.

3. Data and Method

The main data come from the Carnegie Mellon Survey (CMS) of R&D managers, administered in 1994 (Cohen et al., 2000). The population sampled is R&D units located in the U.S. conducting R&D in manufacturing industries as part of a manufacturing firm. The sample was randomly selected from the eligible labs listed in the Directory of American Research and Technology (Bowker, 1995) or belonging to firms listed in Standard and Poor's COMPUSTAT, stratified by 3-digit SIC industry.[3] The survey asked R&D lab managers to answer questions with reference to the "focus industry," defined as the principal industry for which the unit was conducting its R&D. The survey received 1478 valid responses, with an unadjusted response rate of 46% and an adjusted response rate of 54 %.[4] The survey data are supplemented with published data on firm sales and employees from COMPUSTAT, Dun and Bradstreet, Moody's, Ward's and similar sources.

For the analysis in this paper, we restricted our sample to firms whose focus industry was in the manufacturing sector and which were not foreign owned and had at least $5,000,000 in firm sales, or business units (defined as a firm's activity in a specific industry)

[3] Fortune 500 firms are oversampled.

[4] A nonrespondent survey allowed us to estimate what percent of nonrespondents were not in the target population. The results showed that 28% of nonrespondents were ineligible for the survey because they either did no manufacturing or did no R&D. Excluding these from the denominator, as well as respondents who should not have been sampled, yields an adjusted response rate of 54% of eligible respondents.

of at least 20 people, yielding a sample of 1122 cases.[5] We also used patent data from NBER patent dataset (Hall et al., 2001) which were matched to each CMS R&D unit (Roach and Cohen, 2010). Table 1 gives the descriptive statistics on the sample.

3.1. Dependent variables

Innovativeness. We use the term "innovativeness" to mean the relative success of the firm in introducing product innovations. This measure is based on a self-reported scale. The self-reported innovativeness represents a firm's innovativeness against others in its industry at the same time. The CMS asks respondents at what rate product innovations have been introduced by their firm in the period 1991-1993, compared to all other firms in their focus industry that sell in the U.S. market. There were five response categories: substantially above average, slightly above average, average, slightly below average, and substantially below average. We used a five-point ordinal variables ranked from the lowest (=1) to the highest (=5) innovativeness. While this measure has the advantage of measuring the relative strategic advantage of the responding R&D unit in introducing product innovation, it has the limitation of being a self-reported measure and should be interpreted with this caveat in mind. Below we do some checks on the validity of this measure by showing that it is highly correlated with R&D employees (net of firm size) and number of R&D rivals (negatively), suggesting that this self-reported measure is reflecting the underlying concept of relative R&D unit innovativeness.

[5] We also excluded 41 cases where the number of R&D employees was reported to be greater or equal to the number of total employees in their business unit, and 2 cases where the number of business unit R&D employees is zero, which we suspect are errors. The results are qualitatively similar even if we include these cases.

Patents. As an additional measure of innovativeness, we used the number of granted patents from the NBER patent database, which were matched to each CMS R&D unit based on paired lab names and addresses (see Roach and Cohen, 2010).[6] The data are composed of a count of the number of granted patents per responding R&D lab in each year from 1991 to 1994. We used the total count of patents of each respondent over the period of 1991 to 1994. Rather than using firm-level patent counts, we are using business-unit patents, to more closely reflect the impact of business unit structures and environments on business unit innovation. Furthermore, by using both subjective and objective measures of innovativeness, we can show how robust our models are to different measures with different biases.

3.2. Explanatory variables

Integration. The CMS asks the R&D managers to report which methods they have used to facilitate interaction among different functions. There are four methods listed: a) rotation of personal across functions, b) project teams with cross-functional participation, c) interdepartmental committees, and d) computer networks with electronic mail, bulletin board or conferencing capabilities (as the data were collected in 1994, use of this technology was not yet broadly institutionalized). We summed the number of methods used by respondents to measure the level of integration. The maximum is four and the minimum is zero. This measure assumes that the use of more coordination mechanisms means a higher level of integration, (cf. Lawrence and Lorsch, 1967a). However, we also tested those four coordination mechanisms separately and together to allow for variation in the integrative

[6] We thank Michael Roach for providing these data.

power of each mode and for comparison with our aggregate measure.

Appropriability regime. Different industries are characterized by greater or lesser emphasis on particular mechanisms for protecting the returns to their innovations (Cohen et al., 2000). The CMS asks respondents for what percent of their product innovations each appropriability mechanism --- secrecy, patent protection, lead time, complementary manufacturing capabilities and complementary sales/service --- was effective in protecting their firm's competitive advantage from those innovations in the period 1991-1993. There are five response categories: 1) below 10%, 2) 10-40%, 3) 41-60%, 4) 61-90% and 5) over 90%. In our analysis, we created an industry-level measure to represent the responding firm's appropriability environment for that business unit. To obtain the variable, we calculated the means by industrial category (classifying industries by International Standard Industrial Classification (ISIC) , rev. 3 codes) using the mid points of each response category as the value for responses in that industry. For this analysis, we used secrecy, and created a dummy variable called *High_secrecy* which is 1 if the industry mean for the use of secrecy for that firm's industry is greater than 50% and 0 otherwise.[7] Therefore, *High_secrecy* reflects a group of high secrecy industry sectors.

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[7] Here we report industry means and estimate industry fixed effects at a two or three digit ISIC level (33 industries). For estimating industry means for industry-level secrecy, we used a more detailed (generally 3-digit and sometimes 4-digit ISIC), yielding 65 industry sectors, in order to get a more fine-grained estimate of the business unit's environment and to reduce collinearity problems. The detailed process to create *High_secrecy* is as follows. First, we calculated the means of secrecy percentages by industry (= industrial means) using the mid points of each response category: 5%, 25%, 50%, 75%, 95%. In this process, missing data are not valid. Therefore, respondents who have missing data are not considered for calculating their industry mean. Second, we reassigned the industry mean to all respondents in the industry category. Hence respondents in the same industry category all have the same value of secrecy reflecting the prior work by Cohen et al. (2000), since we are interested in the environment in which the firm operates. In this process, respondents with missing data are also given the value equal to their industry's mean. Third, we categorize respondents' industries with their means greater than 50% (the overall mean) into the high secrecy industries and the industries with their means less than or equal to 50% into the low secrecy category. If an industry mean is greater than 50, *High_secrecy* is 1 and otherwise 0.

3.3. Control Variables

R&D employees. The CMS asked about the number of professional and technical R&D employees in their business unit. For analysis, we used the natural log of the number of R&D employees. R&D employees are highly correlated with R&D spending but have lower item non-response. We also control for overall firm size (see below).

No. of rivals. Our dependent variables measure relative performance. A respondent's relative performance may be lower if it has many innovating rivals. Therefore, we controlled the number of "technology" rivals. The CMS asks respondents how many firms are able to introduce competing innovations in time to effectively diminish their firm's profits from their innovations, that is, the number of competing innovators. There are six response categories: 1) 0, 2) 1-2, 3) 3-5, 4) 6-10, 5) 11-20, and 6) >20. We used the mid points of each category (i.e., 0, 1.5, 4, 8, 15.5, and 25).

Goal similarity. To control for competition, we also consider the percentage of projects started by the R&D unit in the period of 1991 to 1993 that have the same technical goals as an R&D project conducted by at least one of their competitors. There are five response categories: 1) 0%, 2) 1 - 25%, 3) 26 - 50%, 4) 51 - 75% and 5) 76 - 100%. We used the mid points of each response category.

Firm Size. The size of an organization and structural differentiation are correlated (Blau, 1970). Therefore, we controlled for the size of firms measured by the natural log of the number of total employees in each firm, to control for underlying differences in the expected level of specialization and differentiation.

Industry diversity. We controlled whether the firm operate in a single industry or more than one industry as an additional proxy of structural differentiation. This is a dummy variable with 1 if the firm operates in more than one industry and 0 otherwise.

Business unit age. We also controlled for the age of business units measured by the natural log of the difference between 1994 and the beginning of that business unit, since older business units may be less innovative overall.

Industry dummies. We used industry sector fixed effects built on the International Standard Industrial Classification (ISIC) codes (Rev. 3).[8] The reference group is miscellaneous manufacturing.

Reasons of patenting & Patent propensity. Firms do not apply patents only for protecting their commercialized innovations (Hall and Ziedonis, 2001, Cohen, et al. 2000), for example, to block others from patenting, to prevent infringement suits, to measure engineers' performance, for use in cross-licensing, etc. Because there are many diverse reasons for patenting, in order to have patent counts more accurately reflect underlying innovation, we should control for a firm's patenting strategy. We have dummy variables for each of the following reasons to patent for product and process innovation respectively: i) to measure the performance of R&D personnel; ii) to obtain revenue through licensing the invention; iii) to improve their position in negotiations with other firms; iv) to prevent patent infringement suits against their firm; v) to prevent other firms from copying their invention; vi) to prevent other firms from patenting a related invention; and vii) to enhance the reputation of the firm or its R&D employees. Moreover, not all innovations are patented and firms (and

[8] Although we used 65 industry sectors when creating the *High_secrey* variable, we used aggregated industry sectors of industry dummies to avoid multicollinearity.

industries) vary in their propensity to patent. Therefore, we also control for the percentage of respondents' R&D unit's product and process innovations for which the firm applied for patents, based on questions from the CMS. These controls for patenting strategy help us separate patents as a measure of innovation from patents as a reflection of firm strategy (Kortum and Lerner, 1999; Cohen, et al., 2002; Hall and Ziedonis, 2001).

Table 1. Descriptive Statistics

	Variables	N	Mean	Min	Med	Max	STD
1	Self-reported Innov.	1109	3.65	1	4	5	1.18
2	No.of patents	1048	22.62	0	1	2857	127.50
3	Integration	1115	2.63	0	3	4	1.08
4	Rotation	1116	0.46	0	0	1	0.50
5	Cross-func. team	1116	0.86	0	1	1	0.34
6	Interdep. committee	1115	0.80	0	1	1	0.40
7	Computer network	1116	0.50	0	0.50	1	0.50
8	High secrecy	1122	0.51	0	1	1	0.50
9	BU R&D employees	1057	247.13	1	20	5000+	1057.70
10	Industry diversity	1081	0.57	0	1	1	0.50
11	Firm size	1104	21359.15	2	3000	100000+	61368.51
12	BU age	1008	49.25	1	42	262	35.47
13	No.of rivals	1020	3.80	0	4	25	4.24
14	Goal similarity	981	53.49	0	63	88	25.19

Table 2. Self-reported innovativeness

Self-reported innovativeness	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Substantially above average	328	29.58	328	29.58
Slightly above average	311	28.04	639	57.62
Average	286	25.79	925	83.41
Slightly below average	118	10.64	1043	94.05
Substantially below average	66	5.95	1109	100.00
Frequency missing = 13				

Tables 1 and 2 give the summary statistics for our measures. The tables show that the mean and median of self-reported innovativeness is "slightly above average". This is to be expected, since the sample is firms that do R&D, which represents a more innovative subset of all firms in an industry. There is also likely to be some response bias in this variable.

We will also use the number of patents in the period of 1991 to 1994 as the other measure of innovative performance, although this measure has its own limitations. These two measures of innovativeness are correlated with a correlation coefficient of 0.14 (partial correlation between self-reported innovativeness and natural log of (no. of patents +1), controlling for industry). Respondents received 23 patents on average over the four years. The average business unit has 247 R&D employees.[9] R&D employees are correlated with self-reported innovativeness and with patent counts (Table 3). Our descriptive statistics in Table 1 also report the characteristics of the explanatory variables. We can see that firms use more than two integrative mechanisms on average (=2.6). The mean size of firms is 21,359 employees. The mean age of business units is 49 years old. Firms and business units in our sample are, on average, large, established organizations, which suggests that integrating across function may be problematic. Respondents have 3 competitors and 53% of goal similarity on average. Table 3 reports the correlations among our variables. Table 4[10] provides means of R&D intensity[11], patent productivity[12], and percentage of product innovations effectively protected by secrecy in each industry sector. In our sample, precision instruments show the highest mean R&D intensity (= 12.20), followed by miscellaneous chemicals, computers, and communications equipment. The lowest mean R&D intensity is printing/publishing (= 0.70), with metal, textiles, and steel also having relatively low R&D intensity. The rankings by patent propensity are somewhat different. In part, this is because the number of patents

[9] The descriptive statistics of business unit R&D employees, firm size, and business unit age in Table1 are from raw data before transformation into natural logs.

[10] For this table, we recoded high extremes equal to the value of the 95th percentile and low extremes equal to the value of the 5th percentile for the number of business unit R&D employees, the number of business unit total employees, the number of granted patents during 1991 to 1994, and firm total sales, and then computed R&D intensity and patent productivity.

[11] R&D intensity in Table 4 indicates the industrial means of ratios of the number of business unit R&D employees to the number of business unit total employees weighted by the number of business unit total employees. All values were multiplied by 100 for easier comparison.

[12] Patent productivity in Table 4 is defined as the industrial means of the number of patents to the total sales (unit of $100 mil.) of each firm weighed by firm total sales (unit of $100 mil.). All values were multiplied by 100 for easier comparison.

reflects firm size and the effectiveness of patents, which vary by industry, in addition to underlying innovation. Precision instruments have the highest mean of patent productivity (= 1.55), followed by medical equipment, computers, and drugs. Printing/publishing again has the lowest mean of patent productivity (= 0.02). Both of these measures can be interpreted as measuring "high-tech" versus "low-tech", although patents are driven by other factors in addition to underlying rates of innovation, including firm size and the effectiveness of patents (Griliches, 1990; Cohen et al., 2000). For secrecy, miscellaneous chemicals has the highest use of secrecy for protecting their product innovation (= 69.82%) followed by metals, textiles, and petroleum while printing/publishing is least reliant on secrecy (= 32.50%). As the muffin example suggests, food products also have high secrecy. The average values of industrial means for R&D intensity, patent productivity and secrecy are 4.91, 0.49, and 50.21 respectively.

Table 3. Correlations

Variables	Correlations													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 Self-reported Innov.	1.00													
2 No.of patents	0.05	1.00												
3 Integration	0.13 ***	0.16 ***	1.00											
4 Rotation	0.10 ***	0.13 ***	0.63 ***	1.00										
5 Cross-func. team	0.10 ***	0.07 **	0.60 ***	0.19 ***	1.00									
6 Interdep. committee	0.04	0.03	0.54 ***	0.03	0.25 ***	1.00								
7 Computer network	0.09 ***	0.14 ***	0.69 ***	0.22 ***	0.21 ***	0.15 ***	1.00							
8 High secrecy	0.06 **	-0.01	0.02	0.00	0.02	0.03	0.01	1.00						
9 BU R&D employees	0.16 ***	0.36 ***	0.52 ***	0.35 ***	0.35 ***	0.16 ***	0.41 ***	0.04	1.00					
10 Industry diversity	0.02	0.06 *	0.07 **	0.05 *	0.03	0.03	0.06 **	-0.01	0.13 ***	1.00				
11 Firm size	0.03	0.21 ***	0.36 ***	0.21 ***	0.23 ***	0.13 ***	0.32 ***	-0.06 *	0.54 ***	0.18 ***	1.00			
12 BU age	0.06 *	0.11 ***	0.12 ***	0.05 *	0.12 ***	0.11 ***	0.04	-0.03	0.15 ***	0.02	0.28 ***	1.00		
13 No.of rivals	-0.06 **	-0.01	0.03	0.01	0.01	0.06 *	0.00	0.03	0.06 *	-0.02	0.00	0.02	1.00	
14 Goal similarity	0.09 ***	0.10 ***	0.11 ***	0.07 **	0.04	0.05	0.09 ***	0.00	0.23 ***	-0.05	0.14 ***	-0.05	0.07 **	1.00

Note: ***, **, *: Significant at the 0.01, 0.05 and 0.10 confidence levels.

Note: Partial correlation between self-reported innovativeness and log of No. of patents controlling for industry sectors is 0.14***

Table 4. Mean of self-reported innovativeness, patent applications, and secrecy by industry

Industry	N	RDIntensity	PatProductivity	Secrecy
1500 Food	92	1.26	0.05	58.64
1700 Textiles	22	1.03	0.26	65.45
2100 Paper	31	1.23	0.16	55.00
2200 Printing/Publishing	12	0.70	0.02	32.50
2320 Petroleum	15	4.79	0.45	62.00
2400 Chemicals, nec	65	9.16	0.62	53.52
2411 Basic Chemicals	36	5.38	0.47	47.21
2413 Plastic Resins	26	7.39	0.34	57.40
2423 Drugs	48	8.85	0.93	57.44
2429 Miscellaneous Chemicals	28	10.61	0.70	69.82
2500 Rubber/Plastic	32	6.15	0.29	55.94
2600 Mineral Products	19	3.55	0.65	46.11
2610 Glass	6	2.41	0.12	46.67
2695 Concrete, Cement, Lime	10	2.51	0.08	45.00
2700 Metal, nec	8	0.77	0.62	65.83
2710 Steel	10	1.04	0.59	37.00
2800 Metal Products	48	1.74	0.43	43.07
2910 General Purpose Machinery, nec	71	3.24	0.40	48.84
2920 Special Purpose Machinery, nec	64	4.82	0.44	43.90
2922 Machine Tools	11	6.25	0.83	61.50
3010 Computers	24	9.72	0.98	45.87
3100 Electrical Equipment	23	2.61	0.53	39.09
3110 Motor/Generator	22	2.70	0.75	52.05
3210 Electronic Components	24	2.45	0.22	33.54
3211 Semiconductors and Related	17	6.29	0.57	55.63
3220 Communications Equipment	33	9.71	0.35	47.88
3311 Medical Equipment	69	8.87	1.20	51.34
3312 Precision Instruments	36	12.20	1.55	47.94
3314 Search/Navigational Equipment	37	7.67	0.18	48.24
3410 Car/Truck	9	4.27	0.31	42.22
3430 Autoparts	34	2.05	0.48	52.26
3530 Aerospace	47	8.32	0.36	55.33
3600 Other Manufacturing	93	2.34	0.36	32.77
All	1122	4.35	0.41	51.23

3.4. Analysis Method

As proxies for innovative performance, we used self-reported innovativeness and the number of granted patents. These two measures reflect both the dominant perspective on innovation research before the 1980s and the Schumpeterian perspective after the 1980s (Arundel et al., 2007). The dominant perspective has viewed that innovation was measured by the amount of patents or patent applications led by R&D inputs (Arundel et al., 2007; Giuri et al., 2007). However, patents have problems as a measure of innovation output. Griliches (1990) points out that patent applications rely on economic conditions; that inventions have different patentability and propensity to be patented; and that patents have intrinsic quality variability. Thus, the propensity of patent applications to be granted and the quality of patents have a skewed distribution (Pakes, 1986; Schankerman and Pakes, 1986). Patents or patent applications do not reflect products of inventive or innovative activity, which is created by a small number of valuable patents, and instead may be better interpreted as a measure of the input index of inventive activity (Schmookler, 1951; Griliches, 1990). The re-discovered Schumpeterian perspective has tried to overcome these limitations of the dominant perspective by distinguishing invention from innovation and developing innovation indicators (Arundel, 2007; Arundel et al., 2007; Giuri et al., 2007). Our main dependent variable, self-reported innovativeness, reflects this Schumpeterian perspective although we admit there are also limitations from using a self-reported measure. Using both self-reported innovativeness and the count of patents, we can see how consistent our results are across different indicators.

For the self-report measure, we use the ordered logistic regression models. On the other hand, we modeled a negative binomial regression for patents, as the distribution of patents is overdispersed with its variance significantly larger than its mean (Hausman et al., 1984). Moreover, to test the secrecy environment contingency theory (Hypothesis 2), we adopted the interaction approach. Drazin and Van de Ven (1985) fleshed out the structural contingency theory underlying the fit of context and structure. They introduced three test methods: the selection, interaction, and systems approaches. While the selection approach tests congruence between context and structure, the interaction and systems approaches test the fit of context-structure and performance (Drazin and Van de Ven, 1985). Moreover, the interaction approach analyzes specific pairs of context-structure variables while the systems approach assesses the holistic patterns of context, structure and performance (Miller, 1981; Drazin and Van de Ven, 1985). For testing our first-level contingency (that integration is associated with performance in the high uncertainty context of R&D), we are implicitly adopting a selection approach. However, for testing the explicit (second-level) contingency between the level of secrecy in the environment and the relation between integration and performance (Hypothesis 2), we adopted the interaction approach (Drazin and Van de Ven, 1985).

4. Results

We use these measures to test our hypotheses, comparing results across our two measures of innovation: self-reported innovativeness and patents. We begin by examining the effects of integration on R&D performance, controlling for other predictors of innovation. We also test the effect of integration on performance contingent on the level of differentiation, which is a finding of early contingency theory. Finally, we test for the interaction between secrecy and integration to see if R&D units in high-secrecy environments benefit less from integration, which is a new finding based on contingency theory.

---------INSERT TABLE 5 ABOUT HERE----------------

---------INSERT TABLE 6 ABOUT HERE----------------

4.1 The effect of integration on organizational performance

We begin with our first hypothesis, which is the relation between integration and innovation. For the analysis of the effect of integration, we first test our model using all 1122 cases. Our measure of integration is the sum of the four separate integration modes. However, we also test the individual items separately. Furthermore, since the effect of integration should be most apparent when differentiation is high, we test the models using only large, Fortune 500-sized firms, yielding a restricted sample of 522 cases.[13] Although we used *industry diversity* and *firm size* to control the level of differentiation, looking at the effect of integration limiting to very large firms can be another way of checking the robustness of our findings, because very large firms should have more subdivisions and problems of coordinating those differentiated subunits (Blau, 1970). Although we consider production, marketing, and R&D divisions based on the survey construction, the increasing size of an organization should generate more differentiation even within each division of production, market, and R&D, thereby increasing the need for the integration of R&D units with other units for successful innovative activity. However, large organizations have also likely already developed organizational routines that can restrain R&D units' creativity and radical research due to integrative routines or procedures (Rogers, 1995). The organizational inertia of large established firms can be resistant to change and hinder innovations (Henderson and Clark, 1990). Moreover, internal competition may make R&D units more conservative and limit the effectiveness of integrative mechanisms (Fosfuri and Rønde, 2009). Therefore, integration might have a negative effect on innovative performance in large enterprises, implying independent, less integrated R&D units (such as

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[13] Fortune 500th firm in 1994 is Texas Industries whose sales were $614.3 million. To limit sample to large firms equivalent to Fortune 500 firms in 1994, we selected firms whose sales were greater than and equal to $614.3 million.
(From http://money.cnn.com/magazines/fortune/fortune500_archive/snapshots/1994)

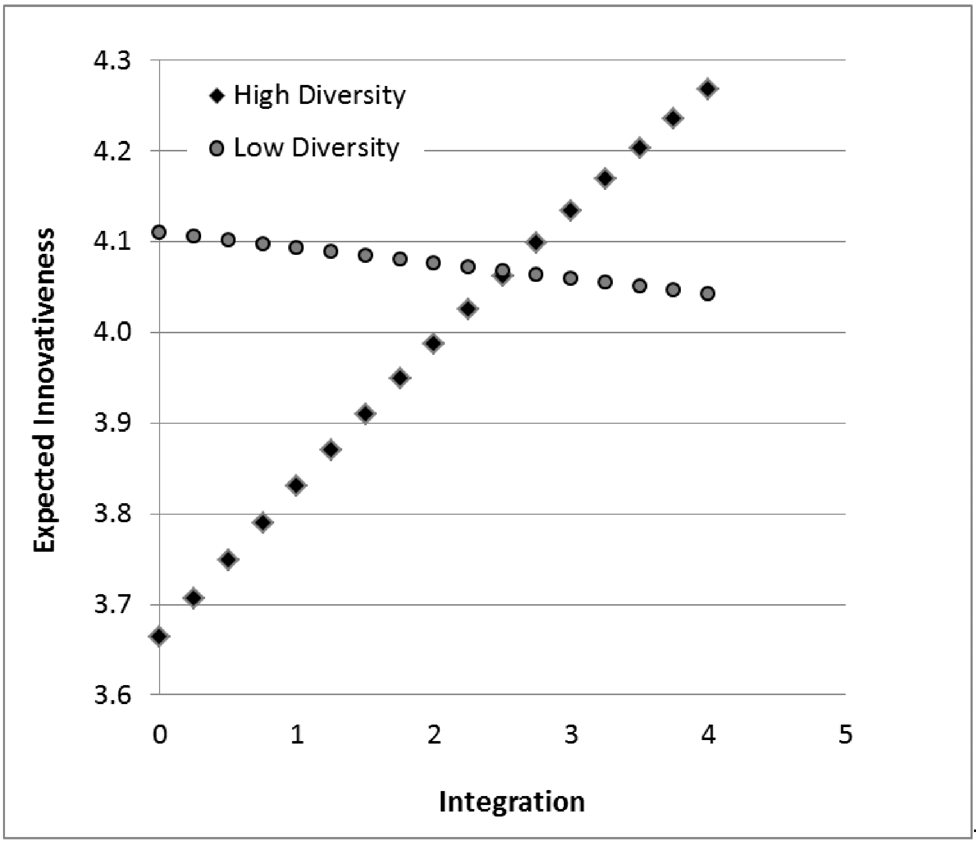
skunkworks) should make greater contribution to innovative performance (H1b). Thus, we will see if the effects of integration are greater or lesser in the large firm sub-sample, to explore the relative impact of differentiation versus bureaucratization. Furthermore, we will see if the interaction effect of integration and industry diversity is positive, again suggesting that integration is especially important in the face of organizational diversity.

Looking at our result, first, the ordered logistic regression and the negative binomial regression for the full sample show that the aggregate measure of integration has a significant positive effect on innovativeness and patents, controlling for industry diversity, R&D, firm size, age, number of rivals and industry, as shown in Model 2 of Tables 5 and 6.[14] Thus, we find support for Hypothesis 1a implying that, on average, integrated R&D units are more effective for innovation than isolated R&D units. We next examine each mechanism separately. Different coordination mechanisms have different purposes and characteristics. March and Simon (1958) categorize types of coordination into coordination by programming and coordination by feedback. Coordination by programming corresponds to impersonal coordination mechanisms such as schedules, official rules and procedures while coordination by feedback includes personal mechanisms such as mutual communication and adjustments through vertical and horizontal channels, and group mechanisms such as scheduled and unscheduled meetings (March and Simon, 1958; Thompson, 1967; Van de Ven et al., 1976; Nihtila, 1999). The form of coordination depends on the nature of the knowledge being shared. Our integration measures are designed to capture this higher-level coordination by feedback, but each mechanism might have greater or lesser effects. Therefore, we check the effect of each mechanism separately, one by one, and then all together. Models 3, 4, 5 and 6

[14] Because of limited cases in a few industries, we collapsed some small industries into miscellaneous, leaving 31 industry dummies for these equations. For the limited sample of very large firms, we had 30 dummies for the self-reported innovativeness equation and 29 dummies for the patents equation. The patent equations also includes controls for reasons to patent product and process innovations and patent propensity.

in Tables 5 and 6 show the effect of the distinct coordination modes on innovative performance. In general, each individual item has only a modest effect. Only rotation has a significant positive effect on innovativeness, and only computer network positively affects patents. When we put the four separate modes all together as shown in Model 7 of both tables, we do not find any critical evidence that those different coordination modes were offset by each other (though some effects are negative in Model 7, they are not significantly so, nor are the standard errors substantially inflated) or that their variation was a serious problem in using the aggregation of the individual mechanisms as a proxy of integration. Therefore, we will use our more robust measure of the sum of integration mechanisms, following prior literature that suggest that using more coordination modes could create a higher level of integration with more integrative opportunities and the synergy effect across coordinative mechanisms.

Figure 1. Interation effect of integration and diversity on innvativeness



Integration is important when the organization is functionally or structurally differentiated. Therefore, the effect of integration should vary by the level of differentiation. We tested the effect of integration contingent on the level of differentiation in two different ways: an interaction approach and a selection approach. First, Model 8 in Tables 5 and 6 presents the effect of the interaction of integration and intra-organization diversity on innovative performance. The significant effect of the interaction between integration and industry diversity shows that the increasing level of integration enhances the expected innovativeness in high diversity firms more than in the low diversity firms. Because of the non-linearities in the ordered logit model (which prevent a simple interpretation of the sign and significance of the interaction term, see Wiersama and Bowen, 2009), we use a graphical representation to show the overall effect of the interaction term, across different values of integration. Figure 1 illustrates the change of expected innovativeness by integration for high and low diversity, which is calculated using predicted probabilities based on Model 8 in Table 5.[15] In Table 6, the effect of the interaction on the number of patents is also positive, although not significant. Second, taking a selection approach, we limit our analysis to the large firms subsample. Model 9 of Table 5 shows that for this sample as well, integration has a significantly positive effect on innovative performance, consistent with the assumption that large firms have more subdivisions and are likely to face problems of coordination, showing further support for Hypothesis 1a (rather than the bureaucratic rigidity argument in Hypothesis 1b). The effect of integration on the number of patents in very large firms is also positive, but not quite statistically significant (p=.11). For both self-reported innovativeness and patents, the impact of integration is even larger for the very large firms (compare Models 2 and 9 in Tables 5 and 6), although the difference from the overall sample estimate is not statistically significant. Overall, the evidence suggests that information and

[15] This graph shows a case of miscellaneous manufacturing (= the reference group of industry dummies) holding all other variables at their means.

coordination benefits from integration improve firm innovative performance.

For controls, as expected, greater R&D effort (controlling for firm size) contributes to higher self-reported innovativeness (giving us more confidence that we are measuring innovativeness) and more patents. The effect of firm size shows the opposite directions in the models of self-reported innovativeness and patents. Firm size has a negative and significant effect on innovativeness (except Model 9 in Table 5[16]) while it has a positive and significant effect on patents. This may reflect ongoing arguments about the relations between firm size and innovative advantage (with large firms being less innovative), and the relations between firm size and patent propensity (see Cohen et al., 2000). In the latter, the positive effect of firm size on patents suggests one of the limitations of patents as a measure of innovation, implying that large firms have higher rates of patenting, perhaps due to a need to protect capital assets (Hall and Ziedonis, 2001) and perhaps due to greater access to resources for patent prosecution, for example, having an in-house patent office (Cohen, et al., 2000). The number of competing innovators affects innovativeness strongly negatively, suggesting that on average a respondent's relative performance will be lower if it has many technology rivals. Goal similarity has a positive significant effect on innovativeness while it has little effect on patent counts. Having a similar goal with competitors could motivate the business unit to move faster to win the competition.

4.2 Integration in high and low secrecy industries

Finally, we hypothesize that the effect of integration is dampened for industries where secrecy is a key appropriability mechanism, because while integration generates

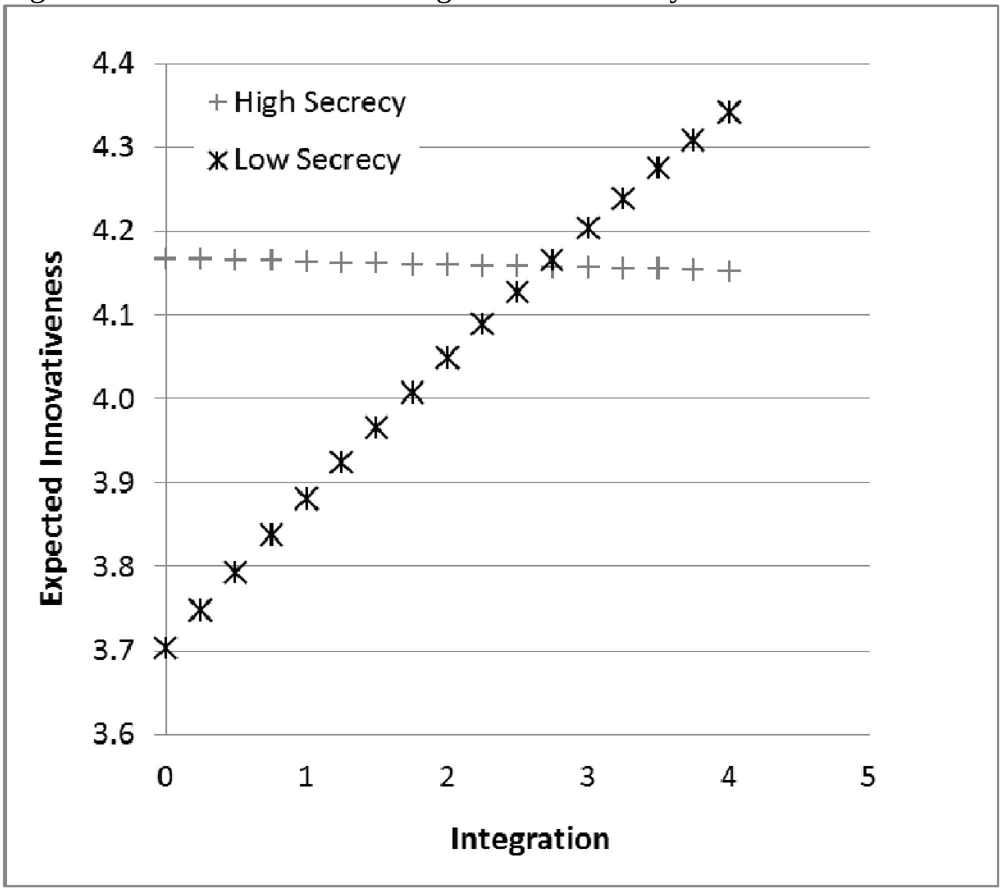
[16] Limited large firms in Model 9 of Table 5 are already large enough to have a variant effect on innovativeness.

connections among people across different work units, it is also likely to increase outflows, resulting in spillovers to competitors (Jaffe et al., 2000). One concern is that firms would not engage in integration if they are in high-secrecy industries, because of fears of spillover. We ran a t-test of integration for high and low secrecy in Table 7 and could not reject the null that the means of integration in high and low secrecy are equal. The means of integration in high and low secrecy environments are very similar (2.65 v. 2.60), suggesting that firms are not organized significantly differently in the two environments, although the effects may be distinct. Thus, firms in both sectors seem to engage in integration. But, because of problems with spillover or unwillingness to share, integration may be less effective in the high secrecy sector.

Table 7. T-test of integration for secrecy categories

	Secrecy		Test statistic
Variable	High	Low	t-value
Integration	2.65	2.6	-0.70

Figure 2. Interaction effect of integration and secrecy on innovativeness



Model 10 in Table 5 shows support for the hypothesis, with the positive effect of integration being weaker in high secrecy industries. Figure 2, which estimates the effect on innovativeness of different levels of integration for high and low secrecy industries, shows that an increasing level of integration enhances the expected innovativeness in the low secrecy environment substantially more than is the case in the high secrecy environment.[17] In other words, the relation between integration and performance is likely to be contingent on the importance of secrecy. When newly developed know-how needs to be kept secret, groups would be more reluctant to share their knowledge even though they are joining integrative activity because the sharing can escalate the risk of disclosure of the secret, thereby risking outflow of their secret to external agents such as imitators and competitors.

[17] This graph shows a case of miscellaneous manufacturing (= the reference group of industry dummies) holding all other variables at their means.

In this case, even though an organization is using diverse integrative methods, it can be less effective for performance because of limited participation by cautious participants. Alternatively, fully-shared information within an organization could leak to external agents such as suppliers, venture capitalists, and competitors in the process of exchanging information for commercialization or partnership, which can result in loss of lead time or being overtaken by competitors building on this knowledge. In Model 10 of Table 6, the contingent effect is not significant for patent counts, although still negative. For an additional robustness check, we test the same model limiting to the count of patents in 1994 (i.e., after the R&D organization data are measures), to address issues of reverse causality. Model 11 in Table 6 presents the results, showing that the effect of integration is even stronger, and the negative interaction effect with secrecy is also larger, though still not statistically significant. Overall, our results suggest that, while integration generally improves R&D performance, the effect is attenuated in high secrecy environments.

5. Conclusions

The results show that intra-organizational integration is important for firm innovation, in particular, in both an uncertain and complex environment and a highly differentiated organizational structure. We also saw that increasing connections among people across their work units may have a down side in the face of R&D competition, because of problems of spillovers (Jaffe et al., 2000). We found that integration may be less effective on innovativeness if secrecy is a key to competitive advantage. Thus, we see evidence that the use of integrative mechanisms may be less effective in some environments (high-secrecy) than others, expanding the findings of Lawrence and Lorsch (1967a, 1967b) and subsequent contingency theorists who have argued that integration was especially important for high uncertainty functions like R&D. We find that the earlier contingency theorists' argument is true, but that there is a second-level contingency, such that the benefit, even for R&D, is dampened in the face of concerns about secrecy. While integration is shown to be important for R&D performance, the effectiveness of these integration mechanisms can vary by appropriability environments (i.e., high secrecy and low secrecy). Thus, our results build on earlier contingency theory models to develop a theory of appropriability regime contingencies as a moderator of the relation between integration and performance. Unfortunately, our measures using survey data have some important limitation. It is possible the range on our variable (0 to 4) was too narrow to clearly see some effects. Perhaps a more nuanced measure might have captured significant interaction effects for patent counts. However, our results are generally robust across different measures of innovation (at least in direction, if not always in statistical significance). Additional work that compares across other measures of innovation are needed to see how robust our findings are to different ways of capturing the concept of innovation.

Integration in our study means knowledge management and coordination through various organizational mechanisms. Formal coordinative methods provide cooperation opportunities across the organization based on tasks for members in different work units bridging their diverse social and technological attributes. However, informal interaction can also provide avenues for building integration within the organization. In particular, bridging different work units through formal devices would be more necessary in an organization where individuals with similar expertise are spatial proximate to each other and distant from those with complementary expertise. Thus, alternative to building integrating structures such as cross-functional teams, organizational geographical proximity (Liu, 2009) can be manipulated to encourage integration to improve information access and firm performance.

The effects of integration, however, will also be differently contingent on the environment in which the organization is involved (Burns and Stalker, 1961; Lawrence and Lorsch, 1967a). Future work needs to look at other factors to further develop our understanding of the environmental factors that condition the relations between intra-organizational integration and innovativeness.

Lastly, we have an open question about whether integration plays a role as a facilitator or an obstacle to the performance of non-R&D units. We only focused on R&D units in this analysis of integration and saw the positive effect of integration on performance of R&D units, which is also a proxy for the innovative performance of firms. These results may not generalize to other parts of the organization. For example, tight links between R&D and manufacturing may interfere with smooth functioning of the production process as R&D continually tries to tinker with production (Burns and Stalker, 1961). Similarly, tight links between sales and R&D may make sales more difficult as R&D employees share ideas for next generation projects with customers that might undermine their willingness to buy the current offerings. Therefore, the analysis of the effects of integration on non-R&D units and overall firm performance will have to be examined by future work.

We see that organizational structures can have important effects on innovative activities. Moreover, these relations are contingent on the appropriability environment in an industry, suggesting that firms need to match their structures to the appropriability strategies that are most effective in an industry. In particular, our results suggest there may be tradeoffs between encouraging inter-unit integration and protecting proprietary information. R&D managers should keep these tradeoffs in mind when designing structures to encourage intra-organizational information sharing. At the same time, the results suggest that, even with this caveat, intra-organizational integration may be a key to encouraging innovative performance.

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Table 5. Ordered logistic regression of self-reported innovativeness

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Ordered logit									Large firms only	
Integration		0.140 *						-0.031	0.258 **	0.290 ***
		(0.072)						(0.099)	(0.114)	(0.096)
Rotation			0.260 *				0.239 *			
			(0.143)				(0.144)			
Cross-func. team				0.367			0.307			
				(0.220)			(0.228)			
Interdep. committee					0.137		0.098			
					(0.167)		(0.173)			
Computer network						0.037	-0.008			
						(0.145)	(0.147)			
Industry diversity	0.039	0.036	0.037	0.037	0.025	0.031	0.037	-0.754 **		0.022
	(0.139)	(0.140)	(0.139)	(0.139)	(0.140)	(0.139)	(0.140)	(0.359)		(0.140)
Integration*diversity								0.297 **		
								(0.125)		
High_secrecy										0.801 *
										(0.418)
Integration*High_sec										-0.297 **
										(0.127)
R&D employees	0.192 ***	0.149 ***	0.164 ***	0.170 ***	0.182 ***	0.184 ***	0.147 ***	0.157 ***	0.118 *	0.146 ***
	(0.048)	(0.051)	(0.050)	(0.049)	(0.048)	(0.050)	(0.052)	(0.051)	(0.067)	(0.051)
Firm size	-0.070 **	-0.079 **	-0.073 **	-0.074 **	-0.070 **	-0.070 *	-0.079 **	-0.084 **	0.006	-0.072 **
	(0.035)	(0.036)	(0.035)	(0.035)	(0.035)	(0.036)	(0.036)	(0.036)	(0.094)	(0.036)
BU age	0.048	0.055	0.053	0.043	0.052	0.049	0.054	0.038	0.254 *	0.058
	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)	(0.090)	(0.090)	(0.137)	(0.089)
No. of rivals	-0.046 ***	-0.048 ***	-0.046 ***	-0.047 ***	-0.048 ***	-0.046 ***	-0.048 ***	-0.047 ***	-0.043	-0.048 ***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.026)	(0.017)
Goal similarity	0.006 **	0.006 **	0.007 **	0.007 **	0.006 **	0.007 **	0.006 **	0.006 **	0.008 *	0.006 **
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	783	779	780	780	779	780	779	779	358	779
Likelihood Ratio	65.792 ***	67.530 ***	68.311 ***	67.603 ***	64.560 ***	65.115 ***	69.547 ***	72.939 ***	67.617 ***	72.852 ***

Note: ***, **, *: Significant at the 0.01, 0.05 and 0.10 confidence levels.

Table 6. Negative binomial regression of patents

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Negative binomial									Large firms only		Limiting to '94 data
Integration		0.158 *						0.084	0.216	0.162	0.340 **
		(0.086)						(0.125)	(0.134)	(0.129)	(0.158)
Rotation			0.037				-0.005				
			(0.166)				(0.168)				
Cross-func. team				-0.001			-0.138				
				(0.377)			(0.387)				
Interdep. committee					0.297		0.268				
					(0.200)		(0.206)				
Computer network						0.341 **	0.318 *				
						(0.163)	(0.166)				
Industry diversity	-0.177	-0.185	-0.179	-0.176	-0.154	-0.209	-0.191	-0.543		-0.183	-0.129
	(0.157)	(0.157)	(0.158)	(0.158)	(0.157)	(0.157)	(0.158)	(0.470)		(0.157)	(0.182)
Integration*diversity								0.122			
								(0.151)			
High_secrecy										-0.036	0.540
										(0.525)	(0.689)
Integration*High_sec										-0.007	-0.172
										(0.154)	(0.195)
R&D employees	0.532 ***	0.496 ***	0.526 ***	0.528 ***	0.515 ***	0.499 ***	0.493 ***	0.496 ***	0.541 ***	0.497 ***	0.558 ***
	(0.056)	(0.058)	(0.056)	(0.057)	(0.056)	(0.057)	(0.058)	(0.058)	(0.087)	(0.058)	(0.068)
Firm size	0.086 *	0.074	0.086 *	0.088 *	0.086 *	0.075 *	0.075 *	0.075	0.065	0.073	0.051
	(0.046)	(0.046)	(0.046)	(0.046)	(0.045)	(0.045)	(0.046)	(0.046)	(0.113)	(0.046)	(0.053)
BU age	0.060	0.076	0.063	0.060	0.059	0.066	0.063	0.071	0.084	0.073	0.100
	(0.101)	(0.100)	(0.101)	(0.101)	(0.100)	(0.100)	(0.100)	(0.100)	(0.150)	(0.101)	(0.120)
No. of rivals	-0.042 **	-0.047 **	-0.044 **	-0.044 **	-0.044 **	-0.044 **	-0.045 **	-0.045 **	-0.032	-0.047 **	-0.048 *
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.029)	(0.021)	(0.026)
Goal similarity	-0.002	-0.001	-0.001	-0.002	-0.002	-0.001	-0.001	-0.001	0.005	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)
Ptnt prop & reasons	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	368	367	367	367	367	367	367	367	185	367	367
Pearson Chi2 (Value/DF)	1.063	1.064	1.068	1.069	1.063	1.074	1.075	1.081	1.039	1.075	1.025
Dispersion	1.265	1.246	1.259	1.259	1.249	1.246	1.239	1.242	1.274	1.246	1.304
	(0.106)	(0.105)	(0.105)	(0.105)	(0.105)	(0.104)	(0.104)	(0.104)	(0.148)	(0.105)	(0.150)

Note: ***, **, *: Significant at the 0.01, 0.05 and 0.10 confidence levels.