In-house Globalization: The Role of Globally Distributed Design and Product Architecture on Product Development Performance

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Changes in the global economy and technological advances are stimulating an increasing geographic distribution of new product design and development efforts. For large organizations that design and develop complex products, this geographic distribution has added a new layer of complexity to product development operations. In this empirical study of a large auto manufacturer, we examine the operational performance implications of splitting the design of vehicle subsystems across multiple geographic locations. Our results indicate that global distribution diminishes the chance of completing tasks on time and degrades subsystem design quality. Finally, by examining the interplay between subsystem centrality and global distribution, we found that higher centrality in the product architecture amplifies the impact of global distribution on subsystem error rates.

Key words: distributed work; global design; product architecture; new product development
History:

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1. Introduction and Literature Review

Geographic distribution of knowledge-intensive work is a widespread phenomenon in the global economy. Companies are increasingly internationalizing their R&D activites (Brockhoff 1998). Open source software such as Linux and Apache is being developed by programming communities that circle the globe (Fuggetta 2003). New product development (NPD) is following manufacturing in being outsourced to internal and external suppliers around the globe. In a survey of 103 new product development firms, 54 had used or were using global teams for some of their NPD efforts (McDonoughIII et al. 2001). The Wall Street Journal recently reported: “Ford Motor Co. is reorganizing its design and engineering centers in a move to make the company more global while speeding vehicle development...the engineering centers, located in different regions throughout the world, will be responsible for development of such components as engines and chassis...” (Bennett 2008).

Firms distribute their product development efforts geographically for several reasons: (1) to reduce labor costs, (2) to acquire technical expertise, (3) to gain access to local markets by incorporating diverse customer values from different cultures, and (4) to increase efficiency by conducting round-the-clock operation. There are at least two key trends that have made distributed NPD practical over the past two decades. One is political, with the opening of many new labor markets to the global economy (Johnston 1991). The other is technological, as CAD systems and collaborative project management software have made it possible to perform design work between distributed teams and coordinate their activities (Leonardi and Bailey 2008).

Despite this significant trend toward geographic distribution of product development efforts, and the recent work of product development scholars that provide insights on issues such as cross-border knowledge transfer (Subramaniam 2006), the role of team member dispersion on teamwork quality and performance (Hoegl et al. 2007), and the use of virtual global teams (Harvey and Griffith 2007); critical questions about the decision to distribute NPD work remain unanswered, including: “Should a company wholly or partially distribute the NPD work?”, “Do the challenges and problems due to globally distributed work offset the benefits?”, “Which metrics should be used to evaluate the success of distributed work?”. These questions are particularly challenging for large organizations that develop large and complex products (e.g., airplanes, automobiles). The critical decision for them is not whether to distribute the design work or not, but rather how to distribute this knowledge-intensive work in the most effective manner. This raises questions such as: “Which parts of the product (e.g., architectural subsystems) should they outsource? Are some subsystems easier to manage and design across geographic boundaries? What is the role of architectural interdependencies in managing global design?”. In this paper, we make use of a large archival data set of the engineering design system of a global auto manufacturer to provide empirical insights into these important questions.

Although it is a relatively new practice, scholars have begun to study distributed NPD from a variety of perspectives. For example, studies of the traditional “make-buy” decision have been expanded to include product design, as well as conventional production decisions (Ulrich and Ellison 2005). These have also considered the effect of learning in product design over time (Anderson and Parker 2002), and the role of uncertainty (i.e., market, creative and process) in NPD planning (Anderson and Joglekar 2005). Although Baldwin and Clark (2000) suggested that outsourcing the components is beneficial to a firm due to increased competition among suppliers, Novak and Eppinger (2001) argued that when the designed product is highly complex, in-house production is preferable due to coordination advantages. Our work diverges from these studies in two major ways: First, instead of examining a high level make-buy decision, which is related to both design and production, we focus specifically on *in-house engineering design* within a large global organization. Although much attention has been given to outsourcing and its consequences, tactical issues resulting from globalization of in-house product development have received little attention Krishnan and Loch (2005). Second, unlike most of the work in this stream, which treat critical decisions such as outsourcing or off-shoring as binary (e.g., either make or buy a part, either offshore a task or not), we develop a more nuanced approach, and provide insights into the partial off-shoring of interconnected subsystems.

To study partial outsourcing or off-shoring of design, we must break products into their consistent parts. The literature on "modularity" does this. Modularity refers to "a special form of design which intentionally creates a high degree of independence or "loose coupling" between component designs by standardizing component interface specifications" (Sanchez and Mahoney 1996). Researchers have pointed out the organizational benefits of product modularity in managing complex product interdependencies (Baldwin and Clark 2000, Schilling and Steensma 2001, Ulrich and Pearson 1998). Product modularity has also been examined from a knowledge-based view of the firm as a driver of modular organization structures. For example, by associating a modular organization structure with a modular product architecture, Sanchez and Mahoney (1996) used modularity as a framework for more effective knowledge management and strategic learning. While studies like these offer insights into the role of product modularity in an organization, little attention has been paid to identifying the right level of modularization (Ethiraj and Levinthal 2004). The most developed approach for matching the organization to a modular product structure is the Design Structure Matrix (DSM) methodology (Eppinger et al. 1994). In this paper, we go beyond the qualitative analysis of DSM to quantify the level of interdependencies between architectural subsystems by using a network-based approach based on social network theory (Wasserman and Faust 1994). We then investigate both the direct effect of architectural interdependencies (i.e., position of a subsystem in the product architecture network) on the on-time performance of NPD work, as well as its moderating effect on the relationship between global distribution of an architectural subsystem and the accuracy of NPD work. In a recent study (Gokpinar et al. 2009), we found that misalignment of organizational communication and product architecture is correlated with warranty claims. In this paper, using the same data source, we focus on the impact of distributed development on on-time performance and process accuracy (error rate) of engineering design work.

Much of the literature that deals with distributed work focuses on the organization rather than the product. Issues such as culture, language, identity, conflict and trust in geographically distributed teams have been examined in great detail in the organizations literature (Jarvenpaa and Leidner 1999, Armstrong and Cole 1998, Hinds and Eds., Hinds and Kiesler 2005). Researchers have examined the role of geographic location on knowledge flow in organizations, and have found that as the geographic distance between individuals increases, transmitting knowledge becomes more difficult (Allen 1977), or equivalently, as the proximity increases, transmitting knowledge becomes easier (Saxenian 1994). Focusing on geographic distance within an organization, Hansen and Lovas (2004) showed that the negative effect of geographic distance (in the form of spatial, cultural, and national differentiation) can be offset by informal relationships of subsidiaries. At the organizational level, Bell and Zaheer (2007) differentiated between institutional and organizational ties, and found that institutional-level ties act as knowledge transmitters if they are geographically proximate, whereas organizational ties do not show this property regardless of proximity. Our paper contributes to the organizational literature on geographically distributed work by: (i) introducing product architecture as a major factor in knowledge transmission across different geographic locations, and (ii) empirically examining the moderating effect of product architecture on the relationship between global distribution of NPD tasks and performance.

In the next section, we develop the theoretical basis for our model, and present our hypotheses. We then provide the details of our setting, and describe our data set and research methodology in Section 3. We present the models, analysis and results of the empirical study in Section 4, and we conclude with a discussion of our findings, their implications, and potential directions for further research in Section 5.

2. Theory and Hypotheses

Global distribution of work affects knowledge flow and performance within organizations through several mechanisms: First, there is a cost associated with coordinating activities in multiple locations. Geographic distance reduces informal and spontaneous conversation opportunities (Allen 1977), formal meetings and face-to-face conferences (Audretsch 2003, von Hippel 1994). While members of physically proximate teams often enjoy social similarity, shared values and expectations (Latane et al. 1995), members of globally distributed teams may find it more difficult to establish such harmonious social environments (Kraut et al. 1998). As a natural consequence of shared values, individuals in close geographic locations find it easier to build trust based relationships (Lawson and Lorenz 1999). Globally distributed teams which have higher cultural diversity, however, experience trouble in building trust among their members (Jarvenpaa et al. 1998, Mayer et al. 1995). In an empirical study on distributed software development, Herbsleb and Mockus (2003) found that distributed work tasks take about two and a half times as long to complete as similar tasks where all the work is collocated. In this paper, we focus on the automotive industry, in which the larger teams, longer development times and physical components involved in vehicle development makes the process quite different than software development. Since one would expect subgroups of a large team to spend significant time working independently anyway, one might think that it would be possible to divide such a team geographically without significant disruption. But because it would be extremely difficult to ensure that geographic distribution follows such natural divisions (if they even exist) and because we expect the social factors noted in the above-cited literature to impact geographically distributed vehicle development teams, we make the following hypothesis.

Hypothesis 1. *The higher the number of global sites involved in a design task, the greater the chance of delay in the task relative to its due date.*

This hypothesis has managerial significance because failure to complete tasks on time can compromise the timeliness of product launches. Many studies have emphasized the importance of speed in the product development process (Stalk and Hout 1990). Furthermore, instead of using absolute task times or surveying engineers to ask how often their work is delayed, as has been done previously in the literature (e.g., Herbsleb and Mockus (2003)), we explicitly calculate task tardiness by using the targeted completion date and actual completion date of tasks from the archival data.

While delay is an important measure of operational efficiency, an equally important measure is accuracy. Unless tasks are completed without errors, products will not meet design specifications. This is because: (i) errors during the design process may lead to quality problems in the end product, and/or (ii) corrective actions in response to errors mean additional costs and loss of valuable time for design engineers. Therefore, we consider the *error rate*[1] as a key performance measure. A design process with both low delay and low error rate is needed to bring high quality, competitively priced products to customers in a timely fashion.

An important way in which organizations avoid errors is through knowledge sharing (Cummings 2004, Haas 2006). However, studies have found that transmission of knowledge within organizations is negatively affected by geographic distance between individuals (Allen 1977). Furthermore, projects that involve team members from different sites experience higher levels of conflict, which is detrimental to performance (Hinds and Bailey 2003). In new vehicle development, where development of each subsystem involves thousands of interdependent tasks, we expect higher levels of conflict to arise in subsystems that are globally distributed than in those concentrated in a small number of sites. These conflicts, along with the difficulties in knowledge transmission, will result in lower performance in performing NPD tasks in glob-

[1] See Section 3.2 for details on how "error rate" is calculated.

ally distributed subsystems[2]. Therefore, measuring the performance of NPD by error rates, we hypothesize that:

Hypothesis 2. *The greater the global distribution score of a subsystem, the higher the error rate for that subsystem.*

Ulrich (1995) defines product architecture as "the scheme by which the function of a product is allocated to physical components" and argues that architecture of a product is important in managerial decision making because it is a key driver of a firm's performance. In contrast, a component is defined as a "physically distinct portion of the product that embodies a core design concept and performs a well-defined function" (Henderson and Clark 1990). For managerial purposes, many design organizations use the word "subsystem" to describe a subset of the product architecture which includes a group of components that collectively perform a higher level function. In a vehicle, examples of subsystems include "front suspension", "steering wheel","door trim", "front seat", etc. These subsystems have many physical interfaces and functional dependencies among their constituent components. If we characterize subsystems as nodes of a network, and link them according to the intensity of interdependencies between them, we can create *product architecture network*. A subsystem with high centrality in the product architecture network is one that has many interdependencies with other subsystems. Because interdependencies complicate the NPD by presenting coordination difficulties at the physical or functional interfaces, we expect a subsystem which is heavily connected to other subsystems in the product architecture network to be more prone to potential design problems. In fact, in a recent study (Gokpinar et al. 2009), we observed that internal errors (i.e., design problems) tend to increase as subsystem centrality increases. But, because resources dedicated to these problems also increase with centrality, and they eventually offset internal errors, we found an inverted U shaped relationship between subsystem centrality and external errors (i.e., warranty claims.) Therefore, we expect to see a positive association between product network centrality and error rates. Thus, we propose that:

Hypothesis 3. *The higher the centrality of a subsystem in the product architecture network, the higher the error rate for that subsystem.*

[2] See Section 3.2 for details on how "global distribution score" is defined as a quantitative measure of the global distribution of a subsystem.

A successful product development project requires substantial collaboration among project group members, such as exchanging information and jointly solving design related problems (Brown and Eisenhardt 1995). Coordination of subsystems whose components are designed across multiple sites is more difficult due to increased geographic distance and knowledge transmission difficulties. We expect these coordination issues to have a deleterious effect on product development performance. We refer to this as the "coordination burden" imposed by geographic distribution of a task. On the other hand, when a firm distributes its product development efforts, it gains freedom in task assignments. In a manner similar to many strategic partnerships, offshoring and outsourcing arrangements (Jarillo 1988, Venkatraman 2004, Metters 2008) in which firms capitalize on the expertise of specialists, we expect to see subsystems to be assigned to those locations with the highest competence (e.g., better technical and labor resources). If this is the case, then we should see a positive association between global distribution and product development performance. We call this the "specialization benefit". Therefore, our conjecture is that, global distribution has two effects on the error rate: the "coordination burden", which increases the error rate, and the "specialization benefit", which reduces the error rate. For central subsystems which have more coordination requirements, we expect the "coordination burden" to dominate, causing the error rate to increase in the global distribution score. However, for peripheral subsystems which have less coordination requirement, we expect the "specialization benefit" to dominate, causing the error rate to decrease in the global distribution score. This leads to our last hypothesis:

Hypothesis 4. *Higher centrality in the product architecture network will amplify the relationship between global distribution score of subsystems and their error rates.*

3. Data and Research Methodology

To test the above hypotheses, we conducted an empirical study of the vehicle development process of a global auto manufacturer. An automobile is a complex product made up of a large number of components, processes and functions. The process of developing a new car involves thousands of people working on thousands of interdependent tasks for many months at multiple locations. These characteristics make the development of a new car an excellent area in which to study management of product development (Clark and Fujimoto 1991). Our study is based on a large archival database of "Engineering Change Orders (ECO's)". ECO's are "part of almost every development process" (Terwiesch and Loch 1999) and they are used extensively in industry to administer and document complex product development projects. Several researchers have described the central role of ECO's in product development efforts (Clark and Fujimoto 1991, Huang and Mak 1999, Loch and Terwiesch 1999).

We spent several months on site to observe and understand the NPD process and to collect and verify the necessary data. Fortunately, recent advances in computer technologies and data storage capabilities have allowed firms to manage and store large amounts of data related to the NPD process. To our knowledge, ours is the first to make use of an ECO database to study globally distributed product development efforts.

Since product design is an iterative process, many changes are made to parts, drawings, interfaces, etc., during the development of a vehicle. All of these iterations are captured via engineering change orders (ECO's). An ECO may indicate a design related problem or mistake, but it may also indicate other issues and transactions as well. For example, other reasons for issuing ECO's include initial release of a part, changes in part specifications due to government regulations or cost-reduction initiatives, and styling changes in response to marketing initiatives. For each ECO, the reason of issuance is indicated by selecting the required reason-code from a drop-down menu. There are approximately 40 reason codes in the system. In addition to the reason code, an ECO contains a rich set of data, including the identity and location of the engineer who initiated it, part numbers associated with it, other parts and design engineers that are affected by the change, and the targeted and actual dates of completion. Our client makes use of a computerized ECO system accessible by design engineers in all of its engineering design sites across the globe. This system facilitates formal communication and collaboration among design engineers at multiple locations.

To facilitate our analysis, we divided ECO's into three subsets according to their reason codes : (i) *new release ECO's*, which are issued for all parts of new models, including both new parts and re-used old parts with new part numbers (ii) *problematic ECO's*, which indicate a design related error, (3) *other ECO's*, which include all other ECO's that are neither new release nor problematic (e.g., ECO's due to exogenous changes in government regulations or styling).

For our study, we examined the entire set of ECO transactions for four global vehicle programs launched in the 2006 model year. Note that, the ECO's to develop 2006 model year vehicles were issued between 2002 and 2005. Also, note that, a vehicle program provides the platform for several models, which may be sold under different brand names in different countries. The four vehicle programs we investigated resulted in eleven new car models, which were jointly designed by design teams from multiple sites across the globe. For the four vehicle programs we studied, the ECO database included the computerized records of almost two thousand design engineers from a total of 10 engineering design centers (all of which are located in different countries, including US, Canada, Mexico, England, and others) working on nearly forty thousand parts. These engineers are responsible for creating and modifying the parts, making sure that they meet design specifications and coordinating interfaces with other parts.

To test our hypotheses, we analyzed this system at two different levels. First, to test Hypothesis 1 about the impact of global distribution on the on-time performance of NPD tasks, we study the system at the level of individual tasks. Then, to test Hypotheses 2, 3, and 4, we study the system at the level of architectural subsystems. We do this by following our client's practice of dividing the vehicle into 243 architectural subsystems, and then evaluating the impact of various factors on error rates in the development of these subsystems.

3.1. On-time performance at the task level

A key dimension of any product development activity is time. To remain competitive in the marketplace, firms are constantly striving for shorter development times. Consequently, product development researchers have employed development time as a critical performance objective (see Gerwin and Barrowman (2002) for a discussion of development time and a list of studies that use it as a performance measure). In a complex product development environment such as vehicle design, in which there are thousands of interdependent tasks, development time highly depends on the on-time performance of individual tasks. Because global design efforts involve tasks that are performed in multiple global locations, we will first create a model to examine the relationship between global distribution of a task and its on-time performance. Our task-level data set includes a cross-section of 28,540 ECO's in four vehicle programs. Note that, each ECO is considered as one task in the design process.

Dependent variable: *ECO lateness.* We measured on time performance by using data from all types of ECO's. As we noted earlier, when an ECO is initiated by a design engineer, a target date of completion is set by the product development managers. If it is completed on or before the due date, it is called *on-time*, if not, it is called *late*. *ECO lateness* is a key metric to assess the performance of NPD efforts at the task level. We measured it with a binary metric, which takes the value of 0 if the ECO is completed on time, and 1 if it is late. We used this binary metric instead of the more conventional continuous definition of lateness (i.e., completion date minus due date) because ECO's differ in terms of complexity, the number of people and parts involved, and other factors that could affect time to completion. Being one day late on a task that was allotted one week to complete is not comparable to being one day late on a task that was allotted one month to complete. So, to prevent task complexity from biasing our results, we measured lateness only in binary fashion. ECO lateness (i.e., on-time performance) is also a key metric used by our client to assess the time-related performance of the engineering design organization.

Independent variable: ***Number of global sites.*** As described in the previous section, when an ECO is issued, all related parts and engineers that will be affected by this change are listed in the ECO. An ECO cannot be completed before getting a sign off from all of the affected engineers, who may be spread over multiple sites. We define the *number of global sites* for an ECO as the total number of different locations of engineers listed on that ECO. Our client has 10 locations in 10 countries for engineering design, so this measure has a range from 1 to 10.

Control variables: Although our main variable of interest is the number of global sites associated with an ECO, other factors may influence on-time performance. Therefore we control for the following factors:

Number of parts. This represents the total number of parts listed in an ECO, which may be an indicator for the complexity of the ECO task.

Number of design engineers. This is the total number of design engineers listed on the ECO, which may negatively affect on-time performance due to communication and signoff delays.

Total duration of the ECO. This variable is calculated by subtracting the initiation date from the completion date. The total duration of the project may be a proxy for the complexity of the task, or it may be the result of the high number of global sites. Nevertheless, we control for this potentially significant effect.

Indicator for the system management group. Our client divides a vehicle into six major system management groups (e.g., Chassis, Electrical, Powertrain). Each ECO is "owned" by one of these system management groups. Since on-time performance may differ across groups, we controlled for it by using $6 - 1 = 5$ indicator variables.

Indicator for the originator country. Although there are clear definitions and guidelines of the process, the practice of initiating an ECO and following it up may differ slightly across different locations, so we control for the originator country of the ECO by using $10 - 1 = 9$ indicator variables.

Indicator for the vehicle program. Issuing an ECO and setting the due dates may also be influenced by the vehicle program it belongs to. Therefore we control for the vehicle programs using $4 - 1 = 3$ indicator variables.

3.2. Error-rate at the subsystem level

While on-time performance at the task level is an important performance measure for NPD projects which is widely tracked in industry, it is clearly not the only one. In addition to timeliness, the other major objective in NPD is quality. To be successful, firms must launch good products in a timely fashion. In this section, we present the variables for our second model, which examines quality in the sense of task accuracy at the subsystem level.

Dependent variable: ***Error rate.*** Design tasks are documented via ECO's. Ideally, each task would be completed correctly the first time. But because errors occur, corrective actions are required; these are documented as problematic ECO's. The fraction of ECO's for a subsystem that are problematic is a measure of the accuracy (quality) of the design process for that subsystem. We call this fraction the *error rate* for a subsystem, and define it as:

$$\text{Error rate} = \frac{\text{Number of Problematic ECO's}}{\text{Number of New release ECO's} + \text{Number of Problematic ECO's} + \text{Number of Other ECO's}} \tag{1}$$

Independent variables:

Product Architecture Network Centrality. We created a product architecture network at the subsystem level in the same manner as (Gokpinar et al. 2009). Specifically, we defined each subsystem as a node, and established weighted link between these nodes by counting the number of co-appearances of two subsystems in the same new-release ECO. Note that, we only made use of new-release ECO's to characterize architectural linkage of parts, because they are issued to initiate *all* parts for a new vehicle program and are not influenced by problems or exogenous changes. Because all parts that have a physical or a functional interface with a given part are listed in that part's new-release ECO, we can get a proxy for the strength of the architectural relationship between two subsystems by counting the number of times they have parts that are named in the same new-release ECO.

After creating the product architecture network, we calculated the *degree centrality* for each node (i.e., subsystem) by using UCINET 6(Borgatti et al. 2002). The degree centrality for each node is calculated as the sum of the weighted links emanating from it. This measure indicates the strength of the architectural connectivity of a subsystem with the rest of the subsystems. More connectivity may indicate more complexity, and hence opportunity for errors.

Global distribution score. We calculated the global distribution of each subsystem by making use of individual ECO's in that subsystem. As we described in Section 3.1, we can identify the number of global sites for each ECO. With these, we calculated the global distribution of a subsystem by calculating the weighted average of all ECO's in that subsystem. That is, if a subsystem has 100 ECO's, of which 20 are associated with one engineering design site, 30 are associated with two sites, 40 are associated with three sites, and 10 are associated with four sites; then the global distribution score for this subsystem is: $[(20 \times 1) + (30 \times 2) + (40 \times 3) + (10 \times 4)]/100 = 2.4$.

Control variables: Other factors that may be associated with subsystem error rate are the following:

Number of parts. As in the previous section, this represents the total number of parts in a subsystem, which may be a proxy for the size or complexity of the subsystem.

Fraction of new parts. This is the fraction of new parts (as opposed to reused parts from an older model) in a subsystem, which may a proxy for overall task difficulty in that subsystem.

Number of design engineers. As in the previous section, this is the total number of design engineers that are listed in the ECO's of a subsystem, which may be a proxy for the complexity of that subsystem.

Number of ECO's. This is the total number of ECO's in a subsystem, which could be an indicator of the size or complexity of a subsystem.

Fraction of late ECO's. This represents the fraction of late ECO's in a subsystem. Using the on-time performance metric for individual ECO's from the previous section, we calculate the fraction of ECO's in a subsystem which are not completed on time. This measure could be an indicator of subsystem-specific overall task difficulty.

4. Models, Analysis and Results

In this section, we describe the model, present the analysis and discuss the results for both of the models described above. We use our model at the ECO-level (task-level) to test Hypothesis 1 in Section 4.1, and then test Hypotheses 2-4 examining the subsystem-level model in Section 4.2.

4.1. On-Time Performance Analysis

Table 1 presents descriptive statistics and correlations for the ECO-level (i.e., task-level) variables. Note that, about 17% of the ECO's are completed late. ECO's are associated on average with 2.87 global sites. The highest correlation is 0.236 ($p < 0.001$), which is between number of global sites and ECO lateness,

Table 1. Descriptive Statistics for ECO Level Variables

	Variable description	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	ECO lateness	0.17	0.39	0	1	1							
(2)	Number of global sites	2.87	1.63	1	7	0.236	1						
(3)	Number of parts	7.64	4.98	1	28	0.024	0.013	1					
(4)	Number of design engineers	8.41	4.05	1	21	0.109	0.087	0.036	1				
(5)	Total duration of the ECO	23.55	7.92	3	131	0.085	0.126	0.009	0.208	1			
(6)	System Dummy-Electrical	0.17	0.39	0	1	0.155	0.071	-0.033	-0.018	0.088	1		
(7)	System Dummy-Powertrain	0.12	0.36	0	1	0.049	0.083	-0.067	0.042	-0.065	-0.021	1	
(8)	Country dummy- USA	0.59	0.61	0	1	-0.162	-0.095	0.051	-0.013	0.017	-0.029	-0.065	1

Table 2. Descriptive Statistics for Subsystem Level Variables

	Variable description	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Error rate	0.345	0.128	0.092	0.705	1							
(2)	Product network centrality x	0.186	0.159	0.084	0.588	0.093	1						
(3)	Global distribution score	2.961	0.873	1.38	5.93	0.156	0.071	1					
(4)	Number of parts	208.7	16.41	136	318	-0.002	0.013	0.008	1				
(5)	Fraction of new parts.	0.319	0.184	0.098	0.625	0.297	0.014	0.011	-0.003	1			
(6)	Number of design engineers	136.7	34.074	39	306	-0.005	-0.028	0.185	0.005	-0.021	1		
(7)	Number of ECO's	265.9	25.76	108	384	0.082	0.169	0.083	-0.016	0.142	0.295	1	
(8)	Fraction of late ECO's	0.198	0. 204	0.045	0.388	-0.181	0.107	0.215	0.010	0.092	-0.119	0.008	1

*Normalized scores

and the relationship is in the predicted direction. This indicates that our estimation is unlikely to be affected by any serious multicollinearity problem.

Because the dependent variable (ECO lateness) is dichotomous (i.e., 1 if late, 0 if on-time), in our analysis we used logistic regression, which is based on the maximum likelihood method. That is, our model predicts the likelihood of ECO's being late for completion. Table 3 presents the results for a stepwise logistic regression at the ECO level. We removed insignificant indicator variables (e.g., dummy for the vehicle program, dummy for the countries except the USA, etc.) from the final model. The slopes estimated in a logistic regression are the natural log of the odds ratio, and therefore, a positive logit indicates a positive association between the independent variable and the likelihood that the binary dependent variable equals one. The sign of the coefficient of our main variable of interest, the *number of global sites*, is positive and significant, which supports Hypothesis 1.

Model 1a provides the results with all variables except the *number of global sites*, while Model 1b presents the final model after adding the *number of global sites* as an explanatory variable. The likelihood ratio test suggests that both models are significant at the 1% level ($\chi^2 = 32.65$ and $\chi^2 = 36.77, p < 0.001$). Also note that, when the *number of global sites* is included in Model 1b, the likelihood ratio χ^2 increases from 32.65 to 36.77. The increase between the χ^2 values of the two models ($36.77 - 32.65 = 4.12$) is also significant at the 0.05 level with $p = 0.0424 < 0.05$ (1 df), which indicates that adding the *number of global sites* improves the model significantly. Also, although the interpretation of the pseudo R^2 in a logit model is not the same as an OLS model (i.e., it does not explain the variation in the dependent variable), it is a widely used goodness-of-fit measure for logit models, and we observed an increase from 0.154 in Model 1a to 0.169 in Model 1b.

The simplest interpretation of Model 1b is that, for every unit increase in the *number of global sites*, the odds of an ECO being late increases by a factor of $e^{0.3254} = 1.385$ units, or alternatively $(1.385 - 1) \times 100 = 38.46\%$. In order to better understand the relationship between the *number of global sites* and the likelihood of an ECO being late, we also examined marginal effect of the *number of global sites* on ECO lateness, which varies with the value of all other explanatory variables. Keeping all model variables at their sample means, we computed the marginal effect of the *number of global sites* on *ECO lateness* to be equal to 0.043 ($p < 0.01$). This implies that a one point increase in the *number of global sites* would increase the probability of late completion of an ECO by 4.3%.

Both the *number of design engineers* and *total duration of an ECO* are significant and positively associated with the probability of a late ECO. This is not surprising, since both of these variables may be indicators of the complexity or difficulty of an ECO. Also, out of the six system indicator variables, only electrical and powertrain systems are significant, and both are positively associated with *ECO lateness*. This is consistent with the intuition of senior design engineers, who suggested that these two systems are significantly more complex, and hence, ECO's in these systems are more likely to be late than ECO's in the other systems, such as body or chassis. An interesting finding is that, ECO's originated in the USA have a higher likelihood of getting completed on-time (i.e., since this variable is significant with a negative coefficient). This may be due to the fact that the ECO system has been employed in the USA longer than other countries, so experience may have played a role. Also, since the USA is the main center for engineering design, with almost half of the entire global design operations, ECO's originated in the USA may have been resolved more efficiently by using the technical resources available at this location.

Table 3. Logit Model for ECO lateness

Variable	**Model 1a**		**Model 1b**	
Number of parts	0.0038	(0.0036)	0.0037	(0.0038)
Number of design engineers	0.0137**	(0.0066)	0.0134**	(0.0064)
Total duration of the ECO	0.0150*	(0.0085)	0.0151*	(0.0086)
System Dummy-Electrical	0.5017**	(0.2324)	0.5009**	(0.2319)
System Dummy-Powertrain	0.3459*	(0.1977)	0.3456*	(0.1975)
Country dummy- USA	-0.4881***	(0.1699)	-0.4878***	(0.1694)
Number of global sites			0.3254***	(0.0894)
Likelihood ratio Chi-square	32.65*** (6df)		36.77*** (7df)	
McFadden pseudo R-squared	0.154		0.169	
n	28,540			
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$				

4.2. Error Rate Analysis

Table 2 provides the descriptive statistics and correlations for the subsystem-level variables. The highest correlation between any of the two explanatory variables is 0.295, which is between the *number of design engineers* and the *number of ECO's*. Again, this suggests that multicollinearity should not be a problem. We note that, both *global distribution score* and *product network centrality* have positive correlations with the *error rate*, as expected. In order to examine the association between these variables and *error rate*, we created a regression model.

We exploited the panel structure of our data set by making use of the 4 global vehicle programs we studied. Specifically, because each vehicle program has 243 subsystems, we were able to observe the cross-section of these 243 subsystems four times each (i.e., one observation per vehicle program). Considering the panel structure of the data, our hypotheses could be tested by creating either a random-effects or a fixed-effects regression model. A random-effects model assumes that the individual effects are uncorrelated with the regressors, and that the individual specific constant terms are randomly distributed across cross-sectional units. This greatly reduces the number of parameters to be estimated, which makes it appropriate for data sets with large cross-sections and small time units (i.e., repeated observations) (Greene 2008). In contrast, a fixed-effects model specifically accounts for the omitted effects which are correlated with the included variables. However, the fixed-effects model, is costly in terms of degrees of freedom lost, since it introduces fixed effects for each cross-sectional unit.

Because our data set included a large cross section of observations (i.e., 243 subsystems), with limited time units (i.e., only 4 vehicle programs), a random-effects model is best suited for our purposes. This was confirmed by the Hausman specification test (Hausman 1978), which we used to decide between a random-effects and a fixed-effects specification, and resulted in a test statistic of $\chi^2 = 6.85$, which is not significant at the 0.05 level ($p > 0.05$). This indicated that the null hypothesis of the random-effects model is not rejected. Therefore, we created a random-effects model using generalized least squares (GLS) method. We used the Lagrange Multiplier (LM) test suggested by Baltagi (2001) to check for autocorrelation in our random-effects model. We found that the limiting distribution is chi-squared with one degree of freedom ($p = 0.149$) which suggests that there is no evidence of serial correlation. Table 4 provides the results of the hierarchical random-effects model for error-rates. Model 2a includes all base variables, while Models 2b and 2c add the *product network centrality* and *global distribution score* separately. Finally, Model 2d includes all variables including the interaction of product network centrality and global distribution score.

Model 2b indicates that product network centrality is significant ($\beta = 0.185, p < 0.05$) and it has a positive impact on the error rate. Moreover, the adjusted R^2 (i.e., the variation in the error rate explained by the explanatory variables) increased from 29.7% in Model 2a to 35.2% in Model 2b. This provides support for Hypothesis 2 that higher subsystem centrality is associated with higher error rates. The *global distribution score* is also significant ($p < 0.01$) in Model 2c, which supports Hypothesis 3. The value of the adjusted R^2 is 37.6% in Model 2c. The implication is that as subsystems get more global, the error rate increases significantly. Finally, in the presence of both the direct effects of *product network centrality* and *global distribution score*, the interaction term *product network centrality x global distribution score* is also significant

Table 4. Random-effects Model for Error Rate

Variable	Model 2a		Model 2b		Model 2c		Model 2d	
Number of parts	0.002	(0.012)	0.003	(0.014)	0.003	(0.013)	0.003	(0.014)
Fraction of new parts	0.788**	(0.342)	0.790**	(0.346)	0.782**	(0.344)	0.785**	(0.347)
Number of design engineers	-0.004*	(0.002)	-0.003*	(0.002)	-0.004*	(0.002)	-0.004*	(0.002)
Number of ECO's	0.002	(0.011)	0.002	(0.010)	0.003	(0.008)	0.003	(0.007)
Fraction of late ECO's	-0.348**	(0.166)	-0.361**	(0.181)	-0.368*	(0.195)	-0.373*	(0.199)
Product network centrality			0.185**	(0.077)			0.176**	(0.083)
Global distribution score					0.042***	(0.013)	0.039***	(0.014)
Product network centrality xGlobal distribution							0.114***	(0.041)
Adjusted R-squared	29.7%		35.2%		37.6%		38.9%	
n	972							

$*p < 0.1, **p < 0.05, ***p < 0.01$

at the $p < 0.01$ level, which provides evidence for Hypothesis 4. The adjusted R^2 also increased to 38.9% when all explanatory variables were included in Model 2d. This supports Hypothesis 4 that product network centrality amplifies the relationship between global distribution score and error rates.

In order to examine the conjectured amplifying effect, we plotted the interaction between *product network centrality* and *global distribution score* in Figure 1. In this plot, both variables take values of one standard deviation above (i.e., high level) and below (i.e., low level) their means. Consistent with Hypothesis 4 and the results of Model 2d, there is a strong positive relationship between global distribution score and error rates when the subsystem has high product network centrality. That is, when highly central subsystems are distributed globally, they experience higher error rates. In contrast, we observe a slightly negative relationship between global distribution score and error rates for low centrality subsystems. That is, when low centrality subsystems are distributed globally, they experience lower error rates. Therefore, the two effects we mentioned in developing Hypothesis 4 in Section 2 play a significant role on the relationship between global distribution score and error rate. This is consistent with our conjecture that the "coordination burden" dominates for highly central subsystems, so error rate increases as the global distribution score increases. In contrast, the "specialization benefit" dominates for low central subsystems, therefore error rate decreases as the global distribution score increases.

Model 4 also reveals that the *fraction of new parts* is a significant predictor of the *error rates* of the subsystems. This is not surprising since new parts imply a learning curve and hence more errors. Also, the *fraction of new parts* may be a good indicator of task difficulty within the subsystems. Interestingly, the

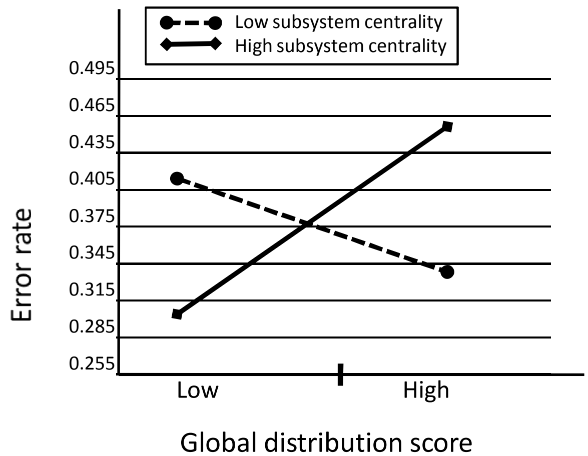

Figure 1 **The impact of subsystem centrality on the relationship between global distribution score and error rate**

number of design engineers is significant but with a negative coefficient. That is, *error rate* in a subsystem decreases as the *number of design engineers* increases. We conjecture that this is a consequence of more engineers in a subsystem providing more pairs of eyes to catch design errors. But our results also imply that this reduction in error rate comes with a price in terms of task delay. That is, the positive association of *number of design engineers* and probability of task delay in Table 3 suggests that more engineers lead to higher task delay. Finally, the *fraction of late ECO's* has a negative and significant coefficient. This indicates that, if engineers in a subsystem are not pressured to completing design tasks on time (resulting in a higher fraction of late ECO's), the designers may be able to achieve a lower rate of errors. That is, this result suggests a trade-off between higher on-time performance and lower error rates.

We conducted several robustness checks of our analysis. First, as with any random-effects model, if the unobserved individual heterogeneity is correlated with the explanatory variables, this may introduce an endogeneity problem, and therefore lead to potentially inconsistent estimates. In order to check this, we also created a fixed-effects model, in which we introduced a dummy variable for each subsystem. We examined the model coefficients of this fixed-effects regression, and found that all estimates are within the 10% confidence interval of our random-effects estimates, and therefore this specification does not change our results.

We also examined the economic significance our our main explanatory variables by changing their values by one standard deviation and calculating the associated effect on the error rates. A one standard deviation unit increase in product network centrality results in a $100 \times [0.159 \times 0.176]/0.345 = 8.1\%$ increase in error rate. Similarly, a one standard deviation unit increase in the global distribution score results in a $100 \times [0.873 \times 0.039]/0.345 = 9.8\%$ increase in error rate. These effects are quite substantial considering the waste and cost associated with making design related errors.

5. Discussion and Conclusion

The impact of globally distributed work, and the role of geographic distance on knowledge transmission, have been studied by management scholars. The focus of these earlier studies has been on the behavioral and cultural characteristics of distributed work and their implications. In this study of global product development efforts, we first created an empirical model to test the operational performance implications of globally distributed design. We found that increasing the degree of global distribution of a design task makes it less likely to be completed on-time. Specifically, our results indicate that globalization leads to delay, not just longer task times, which suggests that management tends to underestimate the impact of globalization on development times when setting due dates. Although one of the reasons for companies to engage in global design activities is to improve operational efficiency, our results suggest that this may not be the case. If a design task is distributed among several global locations, coordination is likely to be a key challenge even in the presence of computerized systems designed to facilitate communication and coordination. Even after controlling for the number of design engineers involved or the system associated with the task, we observed that there is a positive association between the number of global sites involved and the chance of an ECO being late. This association suggests that, managers should be cautious about "going global" with their design organizations, since coordination problems may offset the benefits of distributing design tasks.

Our second analysis examined the role of product architecture and global distribution score on the performance of engineering design efforts at the subsystem level. Our results suggest that the location of a subsystem in the product architecture network may effect the quality of the design work in that subsystem. As a subsystem becomes more central in the network, (i.e., it involves more interfaces and dependencies with other subsystems), the error rate in that subsystem increases substantially. Our study provides an innovative way to measure the strength of these interdependencies via standard data from an engineering change order system. As such, it may help managers to more realistically assess some of complex interdependencies present in their product architecture, and the associated risks of global distribution of design activities.

Our results regarding the role of global distribution of subsystems implies that global distribution is detrimental to design quality. After controlling for such factors as fraction of new parts or the number of design engineers, we found that increasing the global distribution of a subsystem increases leads to higher error rates. Moreover, we found that central subsystems in the product network are particularly vulnerable to this negative effect of global distribution. Spreading central subsystems across multiple design locations is likely to lead high rates of errors. Since these errors are associated with both wasted time (i.e., a part with a design mistake must be re-done), and increased cost (i.e., cost of resources as well as part related costs), product development managers should keep a close eye on highly central and globally distributed subsystems. Indeed, it may make sense not to globally distribute subsystems with high centrality, and instead design them in one or only a few locations. This may help the product development organization better coordinate the many interdependent tasks associated with the highly central subsystems.

Although distributed design has received considerable attention in recent years, our understanding of some forms of distributed organizational arrangements and their performance implications are limited. Research in organizational arrangements such as outsourcing or off-shoring is relatively well-developed, but the phenomenon of in-house globalization has not yet received much attention. Integration of knowledge-intensive operations across multiple global locations, and management of these operations within a firm is a significant challenge that calls for further study by scholars from multiple disciplines. Using a unique data set and innovative metrics, we empirically tested the impact of product architecture and global distribution on design performance. As such, our study extends the knowledge of distributed design efforts and provides insights on the management of product development operations needed to support in-house globalization. This work may also be appealing to product development managers, since we make use of a standard database that is readily available to many product development organizations.

Our work raises several other questions for future research. We examined the role of product architecture and global distribution on product development performance. The impact of these variables on end product quality, as well as the interplay between these product design metrics and manufacturing, could be investigated. Also, we only considered development efforts for one model year, due to data limitations. A longitudinal study that captures the dynamic nature of product design efforts and monitors the improvements over time could be another extension of this work. We employed an archival database for examining the product development process. One obvious direction for future research is complementing this study with more detailed ethnographic studies of distributed work. Another route could be to investigate the informal communication practices of design engineers, and the interplay between geographic location and product architecture on informal communication and performance via a survey instrument. Finally, like many empirical studies, this work primarily relies on data from one company in a specific industry (i.e. automotive) which calls for caution in generalizing our results to other settings and industries.

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